Relationships between musical features and music-evoked emotions and memories

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Objectives

Socioemotional health benefits of music have been recognized for a long time. Especially the ability of music to evoke emotions has led researchers to pay attention to relationships between emotions and specific properties of music. Emotional intensity is also known to be linked to more efficient consolidation and recall of autobiographical memories. Music and autobiographical memories are known to be largely processed by the same neural system, especially in the medial prefrontal cortex. However, the relationship between musical properties and music-evoked autobiographical memories (MEAM) has not been studied before. The first research question of this study was that can some acoustic (musical) features explain the autobiographical salience of the song. The second research question was to determine if that relationship is mediated by subjective emotions evoked by the song, especially the intensity of evoked emotions.

Methods

Participants (n =113, 86 females) were healthy older adults aged between 60 and 86 years (M = 70.72, SD = 5.39). Participants listened 70 song excerpts during the experiment and rated them on valence, arousal, emotional intensity, familiarity, and autobiographical memories evoked by the song. The musical features of the songs were extracted using music information retrieval (MIR) software, followed by principal component analysis. The relationship between musical features and listeners' ratings was assessed using regression analyses.

Main results and conclusions

Lower pulse strength, brightenss, and fluctuation in low-middle frequencies were the best predictors of higher autobiographical salience, familiarity and emotional responses evoked by the songs. The intensity of emotions and, to lesser extent, pleasantness had a mediative effect on the relationship between musical features and autobiographical salience. These results add to the still scarce knowledge about MEAMs in the context of specific musical features.

Avainsanat – Nyckelord – Keywords

music-evoked autobiographical memories, MEAM, familiarity of music, musical features, music information retrieval

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Tiivistelmä – Referat – Abstract

Tavoitteet

Musiikin sosioemotionaaliset terveyshyödyt on tunnettu jo kauan. Erityisesti musiikin kyky herättää tunteita on kiinnittänyt tutkijoiden huomion tunteiden ja musiikin ominaisuuksien välisiin yhteyksiin. Tunnekokemuksen voimakkuuden tiedetään myös olevan yhteydessä niin omaelämäkerrallisten muistojen vahvistumiseen kuin niiden muistista hakemiseenkin. Tiedetään, että musiikkia sekä omaelämäkerrallisia muistoja prosessoidaan suurelta osin samoilla aivoalueilla, erityisesti etuotsalohkon keskiosassa. Musiikin ominaisuuksien ja omaelämäkerrallisten muistojen välistä yhteyttä ei ole kuitenkaan tutkittu aiemmin. Tämän tutkimuksen ensimmäisenä tutkimuskysymyksenä on se, voiko kappaleen omaelämäkerrallista tärkeyttä selittää joillakin musiikin piirteillä. Toisena tutkimuskysymyksenä on selvittää, onko tunnekokemuksella, ja erityisesti sen voimakkuudella, välittävä vaikutus tähän yhteyteen.

Menetelmät

Koehenkilöt (n =113, 86 naista) olivat terveitä, iältään 60-86 vuotiaita aikuisia (M = 70.72, SD = 5.39). He kuuntelivat kokeen aikana 70 katkelmaa musiikkikappaleista ja arvioivat jokaista kappaletta sen herättämän vireystilamuutoksen, tunnekokemuksen voimakkuuden, miellyttävyyden, tuttuuden ja omaelämäkerrallisten muistojen suhteen. Kappaleiden musiikilliset piirteet eriytettiin käyttämällä musiikkitiedonhakuohjelmistoa, jonka jälkeen niihin sovellettiin pääkomponenttianalyysia. Lopuksi, regressioanalyysia käytettiin selvittämään muodotettujen pääkomponenttien ja koehenkilöiden tekemien arvioiden välistä yhteyttä.

Päätulokset ja yhteenveto

Vähäisempi pulssin voimakkuus, soinnillinen kirkkaus ja alemmissa keskitason taajuuksissa tapahtuva fluktuaatio olivat parhaita selittäjiä suuremmalle omaelämäkerralliselle tärkeydelle, kappaleen tuttuudelle ja tunnekokemuksille, joita kappaleet herättivät. Tunnekokemuksen voimakkuus, ja osittain myös miellyttävyys, välittivät musiikillisten piirteiden vaikutusta kappaleen autobiografiseen tärkeyteen. Nämä tulokset lisäävät toistaiseksi vähäistä tietoa musiikin herättämistä omaelämäkerrallisista muistoista tiettyjen musiikillisten piirteiden kontekstissa.

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FOREWORD

This Master's thesis has been made as part of a research project called *Neuroprotective effects of senior choir singing in healthy ageing* based in Cognitive Brain Research Unit (CBRU) of University of Helsinki. The research project focuses on neurocognitive, emotional and quality of life effects of choir singing in the elderly. The data for this thesis has been gathered as a part of the listening task experiment associated with the research program. Fortunately, I got to participate actively for the gathering of the data, which is why I was already familiar with it when starting to work with the analyses. I want to thank my supervisor and the leader of the project Docent Teppo Särkämö and my other supervisor Anni Pitkäniemi for excellent notes and guidance during the writing of this thesis. I also want to thank Pasi Saari for teaching the basics of MIRToolbox and Elina Syrjälä for helpful comments.

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1 Introduction

For the most of us, music is part of our daily life. It has belonged to basically all known human cultures throughout the history (Brown, Merker, & Wallin, 2000). Today, music has many different uses. Aside of invoking purely aesthetic experiences, the emotional power of music is often utilized to affect mood and more generally to create atmosphere, affect cognitive ergonomics (Dalton & Behm, 2007), increase the consumption of certain products (North, Hargreaves, & McKendrick, 1997), or potentially, for controlling risk-taking in certain situations (Halko & Kaustia, 2015; Elvers & Steffens, 2017) to give just a few examples. The healing properties of music have been utilized for a long time in different traditions (Conrad, 2010). In recent decades, scientific research has showed that music can have positive effects in many areas of health care and well-being. Emotional self-regulation is an obvious example of everyday case, where music can help anyone (Saarikallio, 2010). Coronary heart disease patients (Bradt & Dileo, 2009) and patients awaiting surgical procedures (Bradt, Dileo, & Shim, 2013) are examples of groups that could benefit from music listening in terms of stress and anxiety reduction. Music also has uses in neurological rehabilitation, for example in dementia, where musical leisure activities, such as singing and music listening, have been observed to enhance cognitive functioning and mood in persons with dementia and improve the emotional well-being of their caregivers (Särkämö et al., 2014). Aside from persons with dementia, musical activity is also typically used by healthy elderly people as a way to keep up one's activity and abilities, and to get learning experiences and social interaction (Saarikallio, 2010).

1.1 Structure of music

So music in general has many different uses, but there is a huge amount of different kinds of music. Defining exhaustively what music is, is probably impossible or at least very hard (a challenge pursued by many philosophers). It is, however, possible to find some similarities between different kinds of music and establish a set of features that music is typically formed of. The three main perceptual elements of music are time, tonality, and timbre (Janata, 2013). Time, as a musical dimension, consists of properties of rhythm and meter. Meter defines the hierarchy of beats, their relative strengths, inside a bar or other musical structure. Rhythm consists of periodicities and other short-time temporal structures. Tonality refers to pitches (defined by their fundamental frequencies) and their relative structure, like keys and contours. Perception of tonality is culture-dependent, which is why it is sometimes assumed to be learned through statistical learning mechanisms (Tillmann, Bharucha, & Bigand, 2000) and does not appear to show a clear genetic component

(Seesjärvi et al., 2016). Timbre, the quality of a tone, represents how sound is perceived, when tonal and time attributes are held constant. For example, bowed instruments and brass instruments, which have different timbres, sound different to us, even if they are playing the exactly same note. So it is the timbre of a sound that distinguishes instrument sounds from each other.

While music can be roughly described by these three main elements, they could, and in many cases should, be broken down to smaller parts to describe music in detail. Pulse clarity, key clarity and distribution of spectral components, are examples of such finer elements. In this study those smaller parts are hereafter referred to simply as *musical features*. The musical features consist of everything from lower level features, such as changes in loudness, to higher level features, such as clarity of a musical key. These features are thought to be acquired through implicit or automatic learning by a mere exposure to certain kind of music during development (Tillmann et al., 2000).

Because musical features could be defined in quite technical way, it is possible to extract them computationally from musical audio signal, making it possible to analyze them through statistical methods. The techniques developed for this are known as *music information retrieval* (MIR), which is an umbrella term for many different ways to extract information from music, and most typically from musical audio signal. Extracted information could be intuitive in nature, like how clearly the music is played in specific key, or more computational, like the distribution of the overall frequency spectrum. It has been shown in many studies that such computationally extracted musical features could be used effectively as an explanatory variables for musical choices (Barone, Bansal, & Woolhouse, 2017), perceived emotions (Schubert, 2004) and experienced emotions (Gingras, Marin, & Fitch, 2014). However, along with music as a structured sound, different cultural or personal aspects, such as lifetime experiences and societal factors, form together the way we perceive, make and consume music. While it is possible for music to be described in very technical way, the main reason we often listen to music is it’s ability to influence our emotions and mood directly.

1.2 Music and emotions

Music has the ability to modify one’s emotional state, which has led to widespread use of music as an emotional self-regulation tool in everyday context (Saarikallio, 2010), sometimes also in maladaptive way, such as in cases when it is used to express negative emotions (Carlson et al., 2015). The emotion-inducing effect of music has been noted for a long time and it has been a subject of large amount of scientific and philosophical research. In this section, three dimensions of affect that are typically used in the dimensional approach to emotion research, are introduced. Also, some findings about musical emotions in the context of these dimensions are discussed. At the end of the section, I will briefly outline what is currently known about the neural basis of music-evoked emotions.

1.2.1 Pleasantness and arousal

The two classical dimensions of emotional experience are valence (or pleasantness) and arousal. These dimensions of Russell's (1980) Circumplex Model of Affect (CMA), have been the main dimensions explored in many studies where the relationship between musical features and emotions have been in the focus. The CMA proposes that different affective states can be construed along these two dimensions, with valence referring to a continuum from an unpleasant to pleasant (or negative to positive) emotional experience, and arousal referring to a continuum from deactivation to activation (or low to high level of arousal). For example, a frightening event elicits high arousal and negative valence, which creates a physiological and psychological affective reaction that in turn raises heart rate and recruits attention. As an example from a musical context, a lullaby typically elicits low arousal and positive valence, and is therefore experienced as calming and safe. Valence and arousal are considered as essentially independent dimensions (Kuhbandner & Zehetleitner, 2011; Russell, 1980).

It is well-known that musical features influence the emotional experience evoked by music, and that musical emotions can be modelled with the CMA (see for example, Eerola, 2011; Gingras et al., 2014; Schubert, 2004). However, previous results have not all been fully consistent with the CMA, as musical features seem to explain arousal better than valence. For example, in one study, the amount of variance explained by a regression model with musical features as independent variables, was much higher for arousal than for valence (Gingras et al., 2014). In the study of Schubert (2004), valence was explained by some musical features, but the relationships were not as strong as with arousal. On the contrary, changes in arousal have been well explained by changes in some musical features, particularly loudness (Schubert, 2004; Dean, Bailes, & Schubert, 2011).

1.2.2 Intensity of affective experience

Along with valence and arousal, intensity of emotions is an important property of affective experience (Talarico, LaBar, & Rubin, 2004). Russell & Carroll (1999) have included intensity of emotions to the valence to form a bipolar dimension where intensity has a value zero at the center point. In their model, emotional intensity grows as distance from the center grows, independent of direction (towards high or towards low valence). In the context of musical emotions, the strength of emotions seems to be evaluated by overall impression of musical experience (Schäfer, Zimmermann, & Sedlmeier, 2014). However, even single moments of the song can have great impact on the overall emotional evaluation (Fredrickson & Kahneman, 1993).

The relationship between emotional intensity and valence is somewhat complex when studied in the context of memory. Positive (high valence) memories have higher emotional intensity than negative (low valence) memories in healthy subjects, but also in persons with mild cognitive impairment, or mild/moderate dementia (Gorenc-Mahmutaj et al., 2015). Concerning music related emotions, the correlation between strength of emotional experience and positive valence could result from the fact that music tends to evoke more positive memories and also strong emotions (Janata, Tomic, & Rakowski, 2007). In contrast, in currently experienced emotions, negative emotions tend to arouse stronger and longer lasting neural activation in brain regions associated with self-referent processing compared to positive emotions (Waugh, Hamilton, & Gotlib, 2009).

1.2.3 Neural basis of music evoked emotions

The neural processing of musical stimulus starts when a complex sound wave, representing music, reaches the eardrum making it vibrate (Gazzaniga, Ivry, & Mangun, 2002). This vibration is transformed to the neural representation in the cochlea which outputs the signal to the nuclei located in the brainstem and the midbrain. From the medial geniculate nucleus the signal is directed to the auditory cortex, which is organized in a hierarchical manner (Zatorre & Salimpoor, 2013). The lowest level sound information is processed in the core areas of the auditory cortex followed by belt and parabelt areas and some associative cortical areas that are responsible of higher level processing. Those structures are needed to process any auditory information. There is also a degree of functional lateralization between the auditory cortices. The role of the right hemisphere in pitch perception is salient, compared to left hemisphere which is more specialized in tracking time-related components (Zatorre, Belin, & Penhune, 2002; Zatorre & Gandour, 2008; Zatorre & Salimpoor, 2013). Besides that, auditory cortices are an important part in the formation of musical memories. Actually, auditory areas have bidirectional interactive connections to memory and executive systems, which make it possible for the brain to make predictions of music-related events in real time (Zatorre & Salimpoor, 2013). This ability to predict musical events leads to emotional reactions, such as tension, but also to relaxation, giving a feeling of reward (Koelsch, 2014).

The mesolimbic reward system, and especially its dopaminergic receptors, is consistently found to be activated during listening to pleasant music (Koelsch, 2014; Zatorre & Salimpoor, 2013). This indicates that music can elicit the same kind of rewarding response as gambling. Also, the connectivity between the superior temporal gyrus and the nucleus accumbens of the basal ganglia explains some of the individual variation in musical taste, according to Zatorre and Salimpoor (2013) and Koelsch (2014). The superior temporal gyrus contains highly individualized set of connections based on musical experiences. Those connections take part in the formation of musical memories. The nucleus accumbens, in turn, is an important part of the dopaminergic reward system, and also tightly connected to other subcortical areas that process emotions and memory, such as the amygdala and the hippocampus. This is the case especially when processing familiar musical stimulus. Some other brain areas have increased activation during certain kind of music-evoked emotions, such as superficial amygdala while listening pleasant or joyful music (Koelsch, 2014). Because of it's high centrality in the emotion network, amygdala has high importance in modulating emotional experience, such as valence and arousal responses to music (Koelsch, 2014). Hypothalamus has also role in the processing of musical emotions, especially in socially important musical emotions (Zatorre & Salimpoor, 2013) and stress related modulation (Koelsch, 2014).

Unlike visual information, very small amount of auditory information are usually conveyed at single point in time. When a whole picture can be seen in a very short time window, one cannot perceive a meaningful musical excerpt in a blink of an eye. Especially concerning higher level musical features, such as a clarity of a pulse of the song, working memory and other higher cognitive components are needed to combine appropriate musical information over time (Zatorre & Salimpoor, 2013).

Valence of an emotional experience also has a part in music-elicited neural activation. Pleasant and unpleasant musical experiences activate partly different brain areas, pleasant musical experience especially the orbitofrontal cortex and unpleasant musical experience especially the parahippocampal gyrus (Blood et al., 1999). However, their study operationalized pleasant musical stimulus as a consonant one (harmonically relaxed and agreeable) and unpleasant as a dissonant (harmonically rough and tense). This does leave some ambiguity to the results since it is not the case that all people actually perceive all dissonant music as unpleasant (or all consonant music as pleasant). They also found that the brain regions whose activity correlate with music elicited emotional responses are, at least in some cases, distinct from those concerning music perception.

In addition to the valence, arousal and intensity of emotions, the emotional experience evoked by a particular song could also be influenced by listener’s familiarity with it (Ali & Peynircioglu, 2010). Familiarity leads to expectations about the song and to the preparation of emotional neuronal networks by expectation, leading to stronger emotions during listening. Familiarity of music also increases the chance of liking it (Ali & Peynircioglu, 2010), which should increase the experienced pleasantness of the song.

1.3 Music-evoked memories

1.3.1 Autobiographical memory

Autobiographical memories are essential part of our mental well-being. They can be thought of as a personal record of our past life, including events we remember and our personal knowledge (Ford, Rubin, & Giovanello, 2016). However, there exists no precise definition of autobiographical memory (Greenberg & Rubin, 2003). In the present study autobiographical memory is used to mean any kind of memory that somehow relates to person’s own past life, and of which the person is conscious. Definition in this context is wide because people participating in the experiment of this study, which is described later, had to define it by themselves during the experiment.

Autobiographical memories can be classified based on their levels of detail, spanning from event-specific to lifetime periods, or their content, comprising either semantic or episodic knowledge (Janata et al., 2007). There is evidence that music can evoke autobiographical memories related to all levels of detail (Janata et al., 2007), and it is also intuitively clear that many autobiographical memories are episodic in nature. Neverthless, they could also be semantic, and the tendency to recall semantic details of autobiographical memories over episodic ones actually grows as a function of age (Levine, Svoboda, Hay, Winocur, & Moscovitch, 2002). This age-related change is important to take into account, because semantic memory allows our efficient functioning in the real-world environment.

1.3.2 Music-evoked autobiographical memories (MEAM)

By definition, MEAMs are autobiographical memories evoked specifically by music. In other terms, the music acts as a cue that triggers the autobiographical memory processes. Music excites an associative network of neurons that is related to both the music and the autobiographical memories (Janata, 2009). One of the key brain areas in processing self-related memories and music is recognized to be the medial prefrontal cortex (Gilboa, Winocur, Grady, Hevenor, & Moscovitch, 2004; Svoboda, McKinnon, & Levine, 2006; Janata, 2009). Janata (2009) argued that music and autobiographical memories are coupled in medial prefrontal cortex, suggesting that there is an actual neural link between music and autobiographical memories.

Although the medial prefrontal cortex is a highly salient area in music processing, many other brain areas also take part in it actively. For example, the frontotemporal circuit, consisting temporal and lateral prefrontal areas, is important in processing melodic structure, either when heard or explicitly imagined (Jacobsen et al., 2015; Janata, 2013). However, brain areas that store music related memories are largely different from the ones that are in charge when thinking about music consciously (Jacobsen et al., 2015). Areas that store musical memories are some of the areas that are best preserved in people with dementia-related cortical atrophy. This is a potential explanation for why many people with advanced Alzheimer’s disease are still able to recall familiar songs and memories associated with them (El Haj, Fasotti, & Allain, 2012).

Music as a perceptual cue makes it highly possible for an autobiographical memory to be elicited involuntarily. Prior research suggests that involuntary memories are likely to be stronger and more specific than consciously evoked memories (Berntsen, 1998; Berntsen & Hall 2004; El haj et al., 2012). Because of their involuntary nature, this is an important notion especially in the context of MEAMs, although all autobiographical memories have a tendency to be more vivid when elicited involuntarily.

1.3.3 Relationship between MEAMs and the general familiarity of music

The correlation between perceived familiarity of music and MEAMs is documented in prior research literature (Ford et al., 2016; Janata et al., 2007). The relationship between the perceived familiarity of a song and the autobiographical memories it evokes is very intuitive, but may be more complex, as pointed out by Janata et al. (2007). If a song is perceived as familiar, it does not mean that it necessarily evokes autobiographical memories. On the other hand, sometimes music that is not even familiar to listener can evoke autobiographical memories. One possible explanation is that some familiar properties of music, such as genre, could be enough to evoke some autobiographical memories (Janata et al., 2007). Although the relationship between familiarity and MEAMs is probably not simple, moderate correlation between familiarity and MEAMs has been reported (Janata et al., 2007) and the familiarity and MEAMs are also found to activate same brain areas, at least partially (Janata, 2009). The processing of new, unfamiliar music differs from the processing of familiar music mostly in recruiting a more heterogenous set of brain areas (Platel, Baron, Desgranges, Bernard, & Eustache, 2003).

1.3.4 Relationship between MEAMs and musical emotions

Emotions may be one key reason why music is able to elicit so strong memories (Schulkind, Hennis, & Rubin 1999; Proverbio et al., 2015). In general, a strong emotional experience creates strong memories (Kensinger, 2009; McGaugh, 2013) and is better at predicting almost all qualities of autobiographical memories than the valence or the age of the memory (Talarico et al., 2004). Accordingly, songs that trigger more intense emotions also tend to elicit more intense autobiographical memories (Schulkind et al., 1999). Schulkind et al. (1999) found out that aside from familiarity, intensity of emotional responses to music correlated highly with the amount of MEAMs, which could mean that stronger emotions elicit stronger memories, or that stronger memories elicit stronger emotions, or probably, both.

Valence of emotions could also play an important role in the forming of memory for musical events. A strong emotional experience generally increases the probability of an event to be remembered later, but negative emotional events are typically remembered in greater accuracy than positive emotional events (Kensinger, 2009). However, music tends to elicit positive memories, and the emotions related to MEAMs are usually fairly strong (Janata et al., 2007). As an example, nostalgia is an emotion typically evoked by music and with a close relation to autobiographical memories. It is normally considered as having a positive valence, and as a music-evoked emotion it has a wide individual variation concerning neural correlates (Barrett & Janata, 2016), in accord with the wide individual variation in autobiographical memories.

As a conclusion, the existence of relationship between emotional reactions and MEAMs is already well known. The research on the relationship between musical features and emotions have also had a lot of promising findings, as discussed in the section ”1.1 Music and emotions”. However, as far as I know, the effect of musical features to MEAMs are not investigated in any prior studies, which leads us to address the purpose of this study.

1.4 Purpose of the study

This study has two primary research questions. The first question is to find out if the MEAMs elicited by hearing songs could be explained by some set of musical features analyzed by using MIR. The second question is to determine if the relationship between musical features and MEAMs is mediated by music-evoked emotions, especially the intensity of evoked emotions. There is some evidence (Kensinger, 2009) that CMA dimensions (pleasantness and arousal) could also have mediating effect between musical features and MEAMs, so their possible mediating effect is also tested.

2. Methods

2.1 Participants

A total of 113 persons (86 females) were recruited from the participants of a senior choir study. 78 of them were singing in a choir. The age of participants ranged from 60 to 86, with a mean (M) of 70.72 and standard deviation (SD) of 5.39. Only 8 participants reported having no present musical activity (singing solo or in group, playing an instrument or dancing) and 3 of them reported having no musical activity during their lifetime. 83 participants, mostly choir singers, reported having at least one weekly musical activity after age of 60. Participants were divided to two groups, so that both groups had approximately the same age distribution, ratio of males/females, and ratio of individuals who sing in choir/those who don't.

2.2 Procedure

The experiment was based on a web browser application created specifically for this experiment and participants were able to do the whole experiment with their own personal computer, in any place or time they wanted. At the start of the experiment was a short practice part where the participants were able to test the user interface and set the volume to a comfortable level. During the experiment, every participant listened 70 song excerpts. After listening to each song excerpt, the participants gave rating answers (using a 5-point Likert scale) to five questions. The questions were presented one at a time and subjects were not allowed to continue to the next question, or the next song, without responding. However, they were able to listen the excerpt as many time as they wanted during answering. Original questions were presented in Finnish, but Table 1 shows the questions and answer options translated to English. When answering the questions, participants got a chance to tell about memories the song evoked. Participants were able to write them to a text editor or speak them for a recorder included in the program. These qualitative aspects of memories were not analyzed in this study.

Table 1. Questions that were presented to participants to rate the excerpts.

Question	Answer options				
How pleasant did you find the song?	Very unpleasant	Somewhat unpleasant	Neutral (not unpleasant and not pleasant)	Somewhat pleasant	Very pleasant
How strong emotions did the song evoke?	No emotions at all	Weak emotions	Moderate emotions	Strong emotions	Very strong emotions
How did the song affect your arousal state?	Decreased arousal significantly	Decreased arousal a little	Neutral (did not affect arousal)	Raised arousal a little	Raised arousal significantly
How familiar were you with the song?	Unfamiliar	Somewhat unfamiliar	Neutral (not unfamiliar and not familiar)	Somewhat familiar	Very familiar
Did the song evoke many personal memories?	No personal memories at all	Few personal memories	Some personal memories	Many personal memories	A lot of personal memories

2.3 Stimuli

A pilot study with 11 elderly subjects and altogether 225 song excerpts was conducted prior to main study to test the applicability of the procedure and to find the right amount of songs for each list. Based on the pilot data, two lists of 70 song excerpts with relatively balanced song familiarity and autobiographical salience (excluding songs with extremely high or low familiarity and autobiographical salience) were created for the experiment. During the experiment, every participant listened 10 folk songs and 15 songs from each decade from 1950s to 1980s (either from list A or from list B). All of the songs were different, and all selected songs had been some of the most played songs of their genre in the Finnish radio channels during these decades. The songs represent different genres (popular, rock and jazz music) and the language of the songs was either Finnish or English. The whole list of songs is presented in Appendix A.

All audio files were in mp3 -format. For each song, the excerpt was selected manually by researchers to represent the most characteristic and well-known part of the song (chorus, for example). All excerpts were approximately 30 seconds long, a typical length in this kind of experiments, ranging from 18 to 37 seconds. The lengths of the excerpts differed between the songs because each excerpt should have a logical start and ending. 1 second half sine wave fade-in and 3 second fade-out were applied to the start and end of each excerpt respectively.

2.4 Musical features used in the study

The choice of the right musical features to represent the musical excerpts well enough was an important methodological aspect of this study. A lot of research on relationship of emotions and musical features exists. Yet, authors tend to not explain sufficiently well why they have chosen specific features for their studies, and in many cases it remains unknown why a particular set of musical features were used. Unfortunately, there is also not much research on the familiarity of music and MEAMs in the context of musical features. Concerning these parts, the present study is exploratory, and features are chosen to represent different core aspects of music well, including some higher level features (formed of lower level features), some of them known to be good explainers for the relationship between music and emotions.

All musical features were succesfully computed from the audio files and only data from participants who completed the whole experiment were included in the analyses. This procedure resulted as zero missing values in the data. Musical features were computed with MIRToolbox 1.7 (Lartillot & Toiviainen, 2007) in MATLAB R2018a environment. The default sampling rate (44100 Hz) for *miraudio* command of MIRToolbox was used (Lartillot, 2017). It is also a typical sampling rate for mp3-files and high enough to include all frequencies that the human can hear. The data were analyzed using the means of rating variables per song, and means of musical features, computed from the values across frames. After computing the means for all songs, they were pooled to form full data.

In present study, short time features were extracted using a frame length of 0.025 seconds, which is around the commonly used time windows for music information retrieval (Alluri et al., 2012; Tzanetakis & Cook, 2002). For long time features, the same procedure as in Alluri et al. (2012) was applied, and a frame length of 3 seconds was used. For every extracted feature, an overlap of 50% was used for frame decomposition. The short-time and long-time features are presented in Table 2, divided by the respective time window and including a short description of the feature. The next sections provide more precise descriptions of all the features.

Table 2. Chosen musical features divided by corresponding time window.

Short-time features (0.025s)	Description
Attack time	Time from the start of the sound to the first peak of the sound's amplitude.
Spectral centroid	Central tendency measure of the spectrum.
Spectral spread	The ”deviation” of spectral centroid.
Spectral flux	A measure of changes in the timbre.
Sub-band fluxes	A measure of changes in the timbre in a limited, octave size bands.
Flatness	A measure for smoothness of the spectrum.
Spectral entropy	The amount of spectral information in the excerpt.
Roughness	A measure of a dissonance of the sound.
RMS Energy	A measure of a loudness.
Long-time features (3s)	
Mode	A measure of a majorness/minorness of the key.
Key clarity	A clarity of the key.
Pulse clarity	A clarity of the pulse.
Fluctuation centroid	The average frequency of rythmical periodicities.
Fluctuation entropy	A measure of rhythmic complexity.
Novelty	A measure for musical expectancy.

2.4.1 Timbral features

Timbral features are related to ”quality” or ”texture” of a sound (Lakatos, 2000), and are usually computationally represented as a spectrum of a signal. *Attack time* (or sometimes rise time) is an essential part of the specificity of instrument sound and the perception of its timbre (Lakatos, 2000). Attack time is the time from the start of a sound to the peak of the sound's amplitude. For example, drum has a very short attack time and flute has a relatively long attack time. *Spectral centroid* is defined as ”the frequency-weighted sum of the power spectrum normalized by its unweighted sum” (Lerch, 2012, p. 45). It represents the center of gravity of spectral energy. In musical context, spectral centroid is higher when there is more energy in the high notes or the high overtones. Along with attack time, spectral centroid is a central part of the perception of timbre (Lakatos, 2000).

Spectral spread descibes the density of power spectrum around the centroid (Lerch, 2012). It can be described as a deviation of the power spectrum.

Spectral flux represents the average change in the shape of the spectrum between subsequent frames. It is computed by taking the average of absolute differences between two consecutive frames for each decomposed frame (Lerch, 2012). Spectral flux represent fast changes in the timbre. *Sub-band fluxes* corresponds to the spectral flux of a limited bandwith. The present study used 10 channel filterbank introduced by Alluri and Toiviainen (2010). The 10 sub-bands are filtered in octave size bands, the first containing frequencies under 50 Hz, the second containing frequencies from 50 Hz to 100 Hz, the third containing frequencies from 100 Hz to 200 Hz, and so on. For example, high value in the second sub-band flux means a lot of activity between 50 and 100 hertz, possibly caused by active bass instrument in the song.

When studying how features of the musical signal affect some perceived measures, it is important to take into account the noisiness of the signal, since too much noise can potentially reduce the perception of a signal. In this study, I used two features that measure noise, *spectral flatness* and *spectral entropy.* Spectral flatness describes the smoothness of the spectral distribution. Formally, it is the ratio of the geometric mean and the arithmetic mean of the spectrum (Lartillot, 2017). For example, the spectrum of white noise has the maximum theoretical flatness because theoretically it contains the same amount of energy in every frequency. Spectral entropy was chosen because aside from being a measure of noise, it is a feature describing how much information the spectrum of the signal contains. Spectral entropy equals the so-called Shannon entropy (Shannon, 1948) of the spectrum. In case of musical signal, it corresponds to the chromatic complexity of the components in music (Eerola, 2011). Both spectral entropy and flatness have high values when the signal is noisy and low values when the signal is clear.

2.4.2 Tonal features

Tonality refers to the aspects which represent the musical scales and dominant notes used in the song. Harmonic structure is also part of tonality, consisting of the relationships between different frequency components (Downey, 2014). The methods used for the computation of tonal features in this study assume the tonal structure of Western music, although different tonal systems exist. This assumption holds since all songs used in the study are part of Western music tradition.

Mode, as a computational musical feature, assesses a difference between best fitting major key and best fitting minor key (Lartillot, 2017). This approach was selected over another possible approach, the sum of differences in all major and minor key strengths, because only short clips of songs were used as stimuli. *Key clarity* represents the strength of the best fitting key for a song where the best fitting key being the most possible key based on the chromagram of the excerpt (Lartillot, 2017). A higher value in key clarity means a more clear musical key. Low value means that it is not clear in which key the song is played.

Roughness is the only purely harmonic feature used in this study. It measures the sensory dissonance of the sound (Lartillot, 2017). Roughness for the whole excerpt is computed from the pairs of the peaks of the spectrum and taking the average of the dissonance between the peaks. Low roughness corresponds to high consonant harmony. When roughness increases, there is a growing amount of frequencies with short perceptual distance from each other.

2.4.3 Time-related features

Temporal features are computationally challenging. Many computational methods developed for extracting rhythmic features are based on the onsets of notes (Lerch, 2012). Although the same might be true for human perception, humans are better than computers at distinguishing many onsets happening almost the same time and in adjusting for dynamic tempos. Actually, the temporally fluctuating songs used in this study were a reason why tempo, while being central time-related component of music, was left out in this study. However, some other time-related features were covered.

Pulse clarity is a measure of rhythmical clarity (Lartillot, Eerola, Toiviainen, & Fornari, 2008). As can be easily inferred from it’s name, it measures the clarity of a pulse. It is computed from an autocorrelation function that estimates the strength of the beats in music. *Fluctuation centroid* represents the average frequency of rhythmical periodicities (Pampalk, Rauber, & Merkl, 2002; Alluri et al., 2012) and *Fluctuation entropy* is a measure of rhythmic complexity (Alluri et al., 2012). If there are many different rhythms with different periodicities, the value of fluctuation entropy will rise. Fluctuation centroid and fluctuation entropy are, in present study, measuring how rhythmic periodicity and diversity affect listeners.

2.4.4 Other features

There were two features that do not fit well to above categories. *Novelty* is a feature that describes the structural novelty of music. In short, it is a measure of musical expectancy. In other words, it shows how much similarity or dissimilarity there are in the music at different temporal locations. In this study, novelty were assessed by multi-granular approach (Lartillot, Cereghetti, Eliard, & Grandjean, 2013). *RMS energy* models the loudness of the song. Its effect on experienced arousal has been quite robust in former studies (Dean et al., 2011; Schubert, 2004).

2.5 Statistical analyses

Statistical analyses and data handling were carried out with R-language version 3.3.3 (R Core Team, 2017) in RStudio environment version 1.1.463. Distributions were examined visually and with Kolmogorov-Smirnov test. Kolmogorov-Smirnov test was done using the R-package `nortest` (Gross & Ligges, 2015). Multicollinearities were assessed with the R-package `mctest` (Ullah & Aslam, 2017) using VIF and tolerance factors. Principal component analyses were carried out for reducing multicollinearity and parallel analysis was used to test the right amount of components. Both were carried out using the R-package `psych` (Revelle, 2017). Histograms and scatterplots were drawn with the R-package `ggplot2` (Wickham, 2009).

The regression models were created by forward stepwise regression, based on smallest p-value. The reason for using this method instead of bidirectional stepwise regression, was that it ensures that most important single predictors will stay in the model. Testing for regression coefficients in multiple regression was done with the core R packages (R Core Team, 2017). As some authors (Johnson, 2013; Open Science Collaboration, 2015) recently pointed out, when doing many different statistical significance tests, one needs to use at least one order of magnitude smaller p-values than is conventional to reach a reasonable chance of replication for statistically significant findings. That means using p-threshold of 0.005 instead of common 0.05 for example. This is especially true for explorative studies, such as present one, where strong a priori hypotheses can’t be set. This procedure should increase replicability of statistically significant findings, so I used the p-value threshold of 0.005 when interpreting the results of regression analyses.

3. Results

3.1 Subjective ratings

Visual examination of distributions revealed that all rating variables except Familiarity had approximately normal distribution. The distributions are presented in Appendix B. Kolmogorov-Smirnov test p-values for the rating variables are presented in Table 3, along with kurtosis and skewness values. Because Familiarity was very left-skewed and had high kurtosis, it was transformed by reversing and inverting it, as suggested by Tabachnick and Fidell (2014). After transformation, the distribution of Familiarity (skewness = -0.47, kurtosis = 2.28, p = 0.01) had better properties regarding the analyses.

Table 3. Kolmogorov-Smirnov p-values, kurtosis, and skewness for all rating variable distributions.

	p-values	Kurtosis	Skewness
Pleasantness	.30	2.49	-0.19
Intensity of emotions	.30	2.78	-0.35
Arousal	.89	2.90	0.06
Familiarity	<.001	5.09	-1.64
Autobiographical salience	.19	2.68	-0.33

As can be seen from Table 4, all correlations between the rating variables were high, ranging from r = .46 (Arousal – Familiarity) to r = .92 (Intensity of emotions – Autobiographical salience). This indicates a lot of mutual variance between rating variables, and could cause a problem of multicollinearity if multivariate statistics were applied. However, as discussed above, the rating variables are theoretically independent constructs and should be treated so. Thus, variable grouping methods (e.g. principal component analysis, PCA) could not be applied to reduce multicollinearity, without losing much information. That is why multiple regression analysis was used. Scatterplots of the correlations are shown in Appendix C.

Table 4. Bivariate correlation coefficients between all rating variables.

	Pleasantness	Intensity of emotions	Arousal	Familiarity	Autobiographical salience
Pleasantness	1.00	.91	.80	.56	.78
Intensity of emotions	.91	1.00	.73	.71	.92
Arousal	.80	.73	1.00	.46	.65
Familiarity	.56	.71	.46	1.00	.84
Autobiographical salience	.78	.92	.65	.84	1.00

Tests for all the correlation coefficients outside the main diagonal have p-values < 0.001.

3.2 Musical features

Visual examination of distributions of musical features revealed that most of the distributions were approximately normal. The distributions are presented in Appendix B. Although there are a few that were clearly not normally distributed, this is not a concern, because the analysis methods used in present study do not expect normality of independent variables (Tabachnick & Fidell, 2014).

As can be seen from Table 5, there were high intercorrelations between many of the musical features. As high correlations between independent variables can potentially induce multicollinearity, I performed appropriate multicollinearity measures. The variance inflation factor (VIF) values of musical features ranged from 1.23 to 109.15 and tolerance from 0.009 to 0.814. As seen in Table 6, even by the most liberal standards, many of the VIF values were too high and the tolerance values too low for all variables to be reliably used in multiple regression. Therefore, as suggested by Eerola, Lartillot, and Toiviainen (2009), PCA was carried in order to reduce multicollinearity.

Table 5. Bivariate correlation coefficients between all musical features. Only correlations greater than 0.3 are shown and correlations greater than 0.8 are bolded.

	AT	SE	F	RMS	R	SF	SC	SS	SB1	SB2	SB3	SB4	SB5	SB6	SB7	SB8	SB9	SB10	KC	M	N	PC
AttackTime	1																					
SpectralEntropy		1																				
Flatness		.77	1																			
RMSEnergy	-.39	.34		1																		
Roughness		.59		.60	1																	
SpectralFlux	-.34	.62	.39	**.81**	.74	1																
SpectralCentroid		**.91**	**.87**	.33	.50	.53	1															
SpectralSpread		.70	**.92**			.36	**.89**	1														
SubBandFlux_1		.55	.56	.44		.57	.53	.50	1													
SubBandFlux_2		.62	.64	.46	.32	.62	.62	.58	**.89**	1												
SubBandFlux_3		.48	.50	.60	.41	.71	.46	.46	.57	.73	1											
SubBandFlux_4	-.51			.58		.52					.39	1										
SubBandFlux_5	-.38			.46	.37	.49						.59	1									
SubBandFlux_6		.54		.53	.62	.75	.36						.61	1								
SubBandFlux_7		.63		.60	**.80**	**.80**	.47		.35	.39	.39		.37	.75	1							
SubBandFlux_8		.75	.39	.53	.79	.71	.66	.35	.43	.51	.44			.52	**.82**	1						
SubBandFlux_9		**.84**	.75	.47	.67	.63	**.92**	.78	.55	.61	.52			.43	.53	.73	1					
SubBandFlux_10		.72	**.84**	.44	.53	.58	**.88**	**.86**	.52	.58	.48			.40	.42	.51	**.88**	1				
KeyClarity		.33			.31									.39					1			
Mode														.35	.34					1		
Novelty																					1	
PulseClarity		.61	.60		.34	.53	.59	.49	.64	.74	.54				.42	.49	.55	.56				1

Table 6. VIF and tolerance values of musical features

	VIF	Tolerance
Attack time	2.9314	0.3411
Spectral entropy	44.4786	0.0225
Flatness	20.7967	0.0481
RMS energy	5.8521	0.1709
Roughness	7.6616	0.1305
Spectral flux	109.1526	0.0092
Spectral centroid	98.6716	0.0101
Spectral spread	33.0000	0.0303
Sub-band flux 1	7.1517	0.1398
Sub-band flux 2	16.8126	0.0595
Sub-band flux 3	11.7026	0.0855
Sub-band flux 4	9.2570	0.1080
Sub-band flux 5	11.2058	0.0892
Sub-band flux 6	13.5728	0.0737
Sub-band flux 7	14.6928	0.0681
Sub-band flux 8	9.5339	0.1049
Sub-band flux 9	19.4236	0.0515
Sub-band flux 10	16.2071	0.0617
Key clarity	1.8811	0.5316
Mode	1.3523	0.7395
Novelty	1.2281	0.8143
Pulse clarity	4.0375	0.2477
Fluctuation entropy	3.2438	0.3083
Fluctuation centroid	4.1581	0.2405

3.2.1 Principal component analyses

An initial parallel PCA analysis with scree plots yielded a four component model. When inspecting the loadings and communalities of the variables in the four component model, it was clear that this amount of components was not enough to explain sufficient variance regarding all variables. The four component model was also too vague for components to be reliably interpreted as independent variables in regression analysis. Five and six component solutions were tested because they were not far from the threshold used in parallel analyses. The six component model appeared to produce most meaningful components for interpretation when compared to the four and five component models.

Redundancy of spectral flux with sub-band fluxes led to high cross-loadings over all components containing at least moderate loadings to sub-band fluxes. Spectral flux were dropped from the analyses for the sake of simpler models, and principal component analyses were carried again.

Table 7 shows the final principal component loadings of the six component model, including proportion of variance explained by single components, cumulative variance explained by all components, and the proportion explained by a single component from the whole model. Cross loadings, where the musical feature has about the same magnitude of loading to two or more different components, were present in Sub-band flux 8, Sub-band flux 5, Attack time and Key clarity. These features were mainly interpreted as belonging to the component with the strongest loading, but it should be kept in mind that they are affecting quite strongly to the other component too. The proportion of variance (0.81) explained by the whole model was high enough that the components could be used as independent variables in following regression models in reasonable way.

Table 7. Six component solution for musical features using varimax rotation.

	Brightness	High-mid	Pulse strength	Low-mid	Rythmic clarity	Novelty	Communality
Spectral Spread	.92						.92
Spectral Centroid	.91						.96
Flatness	.89						.93
Sub-band Flux 10	.89						.88
Sub-band Flux 9	.84						.90
Spectral Entropy	.77	.47					.88
Sub-band Flux 7		.83					.84
Sub-band Flux 6		.78					.76
Roughness		.74					.79
Sub-band Flux 8	.43	.68					.77
Mode		.64					.52
Sub-band Flux 2	.43		.84				.92
Sub-band Flux 1			.80				.81
Sub-band Flux 3			.72				.80
Pulse Clarity			.64				.77
Sub-band Flux 4				.88			.80
RMS Energy				.71			.81
Sub-band Flux 5		.44		.65			.74
Attack Time				-.62	.50		.74
Fluctuation Centroid					.92		.87
Fluctuation Entropy					-.66		.71
Key Clarity		.43			-.52		.62
Novelty						.88	.80
Proportion var	.25	.17	.14	.12	.09	.05	
Cumulative var	.25	.42	.56	.67	.76	.81	
Proportion explained	.31	.21	.17	.15	.11	.06	

Loadings smaller than 0.4 are not shown to make visual examination easier, because smaller loadings could fade the structure of the model. It should be kept in mind, however, that loadings smaller than 0.4, are still included in principal component scores used as independent variables in regression analyses.

From now on, the principal components are called *musical components*, raising their musical meaning over the mathematical one. The first musical component had strongest loadings for variables that model noise (Flatness, Spectral entropy), high frequencies (Spectral centroid, Sub-band flux 9, Sub-band flux 10), and spread of frequencies across the spectrum (Spectral spread). The most informative label for this component is *Brightness* which is typically used as label for greater relative amount of higher frequencies.

Higher mid-level spectral fluctuation sub-bands (Sub-band fluxes 6, 7, and 8 with frequencies 800-6400 Hz) form the basis for the second musical component. There are also quite strong loadings of Roughness and Mode for this component. For Mode, the reason is probably that major third and its overtones have higher frequencies than minor thirds. Concerning Roughness, the reason for high loading is probably that its logarithm has almost perfect linear relationship with Spectral flux, which were most strongly loaded to this same musical component before being dropped out. Spectral flux, in turn, correlated most strongly with the higher mid-level sub-band fluxes. Since this component is dominated primarily by the higher mid-level fluctuation, it is labelled as *High-mid*.

The third musical component is composed of strong loadings of low frequency fluctuation (Sub-band Fluxes 1-3 with frequencies 0-200 Hz) and Pulse clarity. This component's label will be *Pulse strength*, since low frequencies are usually an important source of information about the rhythmic feeling (Hove, Marie, Bruce, & Trainor, 2014) and pulse clarity clearly contributes to the strength of the pulse. The fourth musical component had the strongest loadings for lower mid-level spectral fluctuation (Sub-band flux 4, Sub-band flux 5), loudness (RMS Energy) and a negative loading for Attack time. This component could be labeled as *Low-mid*, although RMS Energy and Attack time are not straightforwardly related to specific frequency bins. However, the relation of Attack time and RMS Energy might rely on percussive instruments, which usually have shortest attack times. The average shape of the spectrum could depend much of the percussive instruments (Elowsson & Friberg, 2017) and in this sample they could have most energy in 200-800 Hz.

The common feature of the variables loading to the fifth musical component is that they are long-term features. Fluctuation centroid and Fluctuation entropy are both rhythmic features and they have strongest loadings to this component, so this component should is labelled as *Rhythmic Clarity*. Negative loading of Key clarity, which is a tonal feature, is not intuitively clear, but might suggest that songs having a stronger rhythmic clarity are usually not so harmonically rich. The last musical component has a strong loading only on Novelty, so it is simply called *Novelty*. It is the only musical component that clearly represents structural properties of a song.

In Table 8, the musical components are presented along with the songs those had highest principal component scores in the component in question. Also, short description of the possible reason for highest score of particular song in the respecting component are provided. Table 8 is just meant to give some examples to a reader and not being even closely exhaustive description of musical components. Finally, it should be noted that the labels for the principal components are only descriptions of mathematically computed linear combinations, and they do not necessarily reflect any underlying latent phenomenon (Tabachnick & Fidell, 2014). In this context, the labels are used to help the interpretation of the regression analysis results presented next.

Table 8. Songs with highest principal component scores with corresponding musical component and a short description of possible reasons for that.

Musical component	Song with highest score	Description
Brightness	Michael Jackson – Billie Jean	Wide sound of snare drum, and high pitch guitar riffs.
High-mid	Olavi Virta – Sokeripala	High pitch accordion line.
Pulse strength	Carl Douglas – Kung Fu Fighting	A clear, almost electronic sounding drum beat.
Low-mid	Ottawan – Hand Up	Moving bass line and singing voices at specific pitch area.
Rhythmic clarity	Kauko Käyhkö – Rovaniemen Markkinoilla	Very clear and stabile rhythm concerning both, singing voice and instruments.
Novelty	Led Zeppelin – Whole Lotta Love	Sudden change of an instrumentalization.

3.3 Regression analyses

Pleasantness was best explained by a regression model ($F(3,136) = 15.41$, $p < .0001$) with Pulse strength ($\beta = -0.150$, $p < .0001$), Low-mid ($\beta = -0.119$, $p = .0005$), and Brightness ($\beta = -0.121$, $p = .0004$) as the explaining variables. The same musical components were best explainers also for Intensity of emotions ($F(3,136) = 22.23$, $p < .0001$), Pulse strength as the strongest ($\beta = -0.204$, $p < .0001$), and with a difference of Brightness ($\beta = -0.138$, $p < .0001$) entering to a model before Low-mid ($\beta = -0.130$, $p = .0002$). Both models had a moderate effect size, $R^2 = .237$ and $R^2 = .314$

respectively. Arousal was explained by only a single musical component, Pulse strength (β = -0.077, p = .0032), having only marginal effect (F(1,138), p = .0032, R^2 = .054) compared to other subjective ratings. Familiarity had smaller regression coefficients on Pulse strength (β = -0.099, p < .0001), Brightness (β = -0.056, p < .0001), and Low-mid (β = -0.038, p = .0010) than other ratings, as a result of transformation. However, this had only slight influence on the size of the effect, which was actually largest for Familiarity (F(3,136) = 37.81, p < .0001, R^2 = .443). Model explaining Autobiographical salience had also quite large effect (F(3,136) = 31.67, p < .0001, R^2 = .398), having Pulse strength (β = -0.265, p < .0001), Brightness (β = -0.183, p < .0001), and Low-mid (β = -0.115, p = .0013) as explaining variables. Table 9 shows all the regression models mentioned above. Bivariate scatterplots between single musical components and rating variables are shown in Appendix C.

Table 9. Regression models for ratings predicted by musical components.

Rating variable	Musical component	β	p	Adjusted R^2	F
Pleasantness	Pulse strength	-0.150	<.0001	.237	15.41 (<.0001)
	Low-mid	-0.119	.0005		
	Brightness	-0.121	.0004		
Intensity of emotions	Pulse strength	-0.204	<.0001	.314	22.23 (<.0001)
	Brightness	-0.138	<.0001		
	Low-mid	-0.130	.0002		
Arousal	Pulse strength	-0.077	.0032	.054	8.99 (.003)
Familiarity	Pulse strength	-0.099	<.0001	.443	37.81 (<.0001)
	Brightness	-0.056	<.0001		
	Low-mid	-0.038	.0010		
Autobiographical salience	Pulse strength	-0.265	<.0001	.398	31.67 (<.0001)
	Brightness	-0.183	<.0001		
	Low-mid	-0.115	.0013		

β = unstandardized regression coefficient, p = p-value of single variable, Adjusted R^2 = adjusted coefficient of determination, F = F-value of the model (p-value in the brackets).

So all ratings were best predicted by some combination of the three musical components, Pulse strength, Brightness and Low-mid. However, as a somewhat surprising result, all linear relationships of the musical components with rating variables had negative regression coefficients. This indicates that higher values in Familiarity, Autobiographical salience, Intensity of emotions and Pleasantness were explained by a lower pulse strength, narrower spectrum (especially from the high end) and less lower middle frequency fluctuation. Lower Pulse strength also explained higher

Arousal, but only by a marginal effect. Interactions between Pulse strength, Brightness and Low-mid were also tested explaining Pleasantness, Intensity of emotions, Familiarity and Autobiographical salience, but none of them were statistically significant (all p-values between 0.07 and 0.94).

These results could, to some extent, be explained by differences in recording technics and musical conventions at different decades. To test this, the data was divided to blocks based on decades and the previous regression models were applied on them. This procedure masked almost all statistically significant effects, but the trend of negative regression coefficients remained the same. The coefficients lack statistical significancy very probably because of much smaller sample sizes. Table 10 shows all regression coefficients large enough to have $p <= 0.5$, divided by decades. As one can see, 35 of 43 coefficients are negative, which is very unlikely (approximately one from 50000) to come by chance. This is a strong case against the explanation that results of Table 9 are only because of change in recording technics and musical conventions over decades, although some effect with oldest songs (50s and folk) are possible (Table 10).

Table 10. Above created regression models divided to publishing decade blocks and folk songs.

Rating variable	Musical component	50s	60s	70s	80s	Folk
Pleasantness	Pulse strength	0.107 (.34)	-0.157 (.07)	-0.091 (.16)	-0.150 (.22)	-0.083 (.44)
	Low-mid	-0.172 (.03)	-0.127 (.08)		-0.157 (.05)	-0.061 (.50)
	Brightness			-0.162 (.04)	-0.105 (.27)	
Intensity of emotions	Pulse strength	0.146 (.14)	-0.212 (.03)	-0.128 (.06)	-0.231 (.09)	
	Brightness			-0.131 (.13)	-0.091 (.38)	0.148 (.46)
	Low-mid	-0.081 (.26)	-0.152 (.06)		-0.202 (.02)	
Arousal	Pulse strength	0.115 (.18)	-0.104 (.06)		-0.157 (.03)	-0.061 (.40)
Familiarity	Pulse strength		-0.098 (.003)	-0.065 (<.001)	-0.080 (.06)	
	Brightness					0.062 (.22)
	Low-mid		-0.053 (.07)	0.025 (.26)	-0.079 (.004)	
Autobiographical salience	Pulse strength	0.074 (.49)	-0.232 (.02)	-0.140 (.03)	-0.178 (.18)	-0.102 (.42)
	Brightness			-0.126 (.13)	-0.101 (.32)	0.198 (.33)
	Low-mid	-0.058 (.47)	-0.114 (.20)		-0.210 (.01)	

P-values shown in brackets next to regression coefficients.

Mediative effects of the emotional variables on the relationship between musical features and Autobiographical salience were tested and found (Table 11). The mediation was tested by the following procedure: First, already established relationships between the musical components and Autobiographical salience were added to a regression model. Second, the emotional variables were added to the regression model one at a time. Third, the increase in the p-values and decrease in the regression coefficients were noted to see if the mediation effect took place. Partial mediative effects of Intensity of emotions were found on Pulse strength (from β = -0.265, $p < .0001$ to β = -0.081, $p < .0001$) and Brightness (from β = -0.183, $p < .0001$ to β = -0.058, p = .0014), and full mediation on Low-mid (from β = -0.115, p = .0013 to β = 0.190, p = .8499). Pleasantness had some partial mediative effect on the model also, but to a lesser degree, decreasing effects of Pulse strength (from β = -0.265, $p < .0001$ to β = -0.156, $p < .0001$), Brightness (from β = -0.183, $p < .0001$ to β = -0.095, p = .0005) and Low-mid (from β = -0.115, p = .0013 to β = -0.028, p = .2966) by much lower amount. Arousal, on the other hand, did not have a mediative effect at all.

Table 11. Bivariate correlations, regression coefficients and p-values of mediation models for each emotion variable.

Variables	Autobiographical salience	Intensity of emotions	Pulse strength	Brightness	β	p
Intensity of emotions	.92				0.905	< .0001
Pulse strength	-.50	-.42			-0.081	< .0001
Brightness	-.34	-.28	~0		-0.058	.001
Low-mid	-.22	-.27	~0	~0	0.190	.85
Adjusted R^2	F					
.86	219.60 (<.0001)					
Variables	**Autobiographical salience**	**Pleasantness**	**Pulse strength**	**Brightness**	**β**	**p**
Pleasantness	.78				0.732	< .0001
Pulse strength	-.50	-.33			-0.156	< .0001
Brightness	-.34	-.27	~0		-0.095	.0005
Low-mid	-.22	-.27	~0	~0	-0.028	.30
Adjusted R^2	F					
.69	76.69 (<.0001)					
Variables	**Autobiographical salience**	**Arousal**	**Pulse strength**	**Brightness**	**β**	**p**
Arousal	.65				0.930	< .0001
Pulse strength	-.50	-.25			-0.193	< .0001
Brightness	-.34	-.04	~0		-0.172	< .0001
Low-mid	-.22	-.01	~0	~0	-0.118	< .0001
Adjusted R^2	F					
0.68	75.62 (<.0001)					

β = unstandardized regression coefficient, p = p-value, Adjusted R^2 = adjusted coefficient of determination, F = F-value of the model (p-value in the brackets).

4. Discussion

This study sought to establish a relationship between specific musical features and subjective emotions, familiarity, and autobiographical memories evoked by music. The two main findings were the following: First, a set of three musical components, Pulse strength, Brightness, and Low-mid, formed the best explaining models for all five ratings, Pleasantness, Intensity of emotions, Arousal (only Pulse strength), Familiarity, and Autobiographical salience. Second, especially Intensity of emotions, but also Pleasantness to some point, had a mediating effect on the relationship between musical features and Autobiographical salience. These results support prior research findings of facilitative and evoking effects of music on autobiographical memories (Ford et al., 2016; Schulkind & Woldorf, 2005) and emotional experiences (Dean et al., 2011; Eerola, 2011; Gingras et al., 2014; Schubert, 2004). Next, I will address more precisely the effects of musical features on emotional ratings, followed by discussion about MEAMs and mediative effects of emotions on them.

4.1 Emotional ratings

In the present data, Pleasantness and Arousal had stronger linear relationship than expected. This finding does not fit perfectly with CMA (Russell, 1980), where pleasantness and arousal are considered as independent dimensions. It is, however, possible that this is only because music is a quite specific type of stimulius, and usually low-valence emotions evoked by music tend to be low-arousal, and high-valence emotions evoked by music tend to be high-arousal. Also, a strong correlation between Pleasantness and Intensity of emotions indicates that positive music-evoked emotions tend to be more intense than negative ones, possibly because negative emotions are only rarely experienced in the context of music (Coutinho & Cangelosi, 2011; Zentner, Grandjean, & Scherer, 2008). A moderate linear relationship between Familiarity and Pleasantness ratings of music was found in the present study, being a little bit weaker than the relationship between Pleasantness and other ratings. This result is in line with previous findings showing that familiar music is experienced as more likable than unfamiliar music (Ali & Peynircioglu, 2010). Altogether, the high and moderately high correlations between all ratings indicates that when music is perceived as emotionally intense, it is also very probably perceived as pleasant, arousing, familiar and autobiographically salient.

The negative relationship of Pulse strength and Pleasantness is somewhat in line with the findings of Leman, Vermeulen, De Voogdt, Moelants, and Lesaffre (2005). They found that legato, which normally corresponds to a weaker pulse, was a structural cue that predicted the experienced valence of music well. However, in their study, brightness did not succesfully predict changes in valence, opposed to present results where the Brightness component correlated negatively with Pleasantness. These present results are, however, in line with findings of Gingras et al. (2014) which showed that lower average pitch level induces more pleasant musical experience. In some studies, also major mode and consonant harmonies have been associated with more positive and pleasant emotions than minor mode (Scherer & Oshinsky, 1977; Wedin, 1972). Especially concerning mode, the relationship to emotional valence has been quite weak, and were not seen at all in present study. This could be at least partly due to the fact that Mode and Roughness were both masked inside a musical component with high middle frequency sub-band fluxes. It seems that the same set of musical features (weaker pulse, lesser amount of high frequencies and less fluctuation on low middle frequencies) leads also to more intense emotional experience. This is not surprising due to the above mentioned finding that pleasant emotions tend to be more intense in the context of music (Coutinho & Cangelosi, 2011; Zentner et al., 2008).

Concerning the arousal dimension, Pulse strength emerged as the only explaining factor for Arousal in the regression model, although the observed relationship between Pulse strength and Arousal was relatively weak. This finding is, however, interesting because previous studies have shown quite strong evidence that sound intensity can predict perceived arousal (Dean et al., 2011; Schubert, 2004). This result could be partly affected by the component model used in present study or by the fact that the word ”arousal”, and it’s Finnish counterpart, were understood in the different way by different participants. Also, this finding is not fully compatible with the one of Leman et al. (2005) which found that some of the same features that form the Brightness component of the present study did actually predict the ”perceived arousal” of music. However, they studied the perception of emotions and this study is about experienced emotions which may explain the difference in the results.

4.2 Autobiographical memories and familiarity

The regression analyses shed light on the first research question, addressing the possibility that the autobiographical saliency of a song could be explained by musical features. Three musical components, Pulse strength, Brightness and Low-mid, were able to explain around 40% of variance of both the Familiarity and the Autobiographical salience. All musical features had a negative relationship with the Familiarity and the Autobiographical salience, following the same tendency as with the emotional ratings. In other words, songs with a weaker pulse, lesser low middle frequencies and loudness, and lesser high harmonics and high notes, were experienced as more familiar and more memory-evoking. A potential explanation, recording technics and general style of songs during different decades, were also tested and no clear evidence for this explanation were found.

As expected, there was a mediation effect of the emotions between musical features and Autobiographical salience. Intensity of emotions was able to fully mediate Low-mid and partially Brightness and Pulse strength. Adding it to the model was able to raise the explained amount of variance from 40% to 86%. This indicates that emotional intensity elicited by a song seems to be central for evoking MEAMs, independent of the location of that emotion on CMA dimensions. This finding is in line with Janata (2007), Schulkind et al. (1999), and Talarico et al. (2004), as well as also with many studies which concluded that musical features can affect the emotional experience (for example Eerola, 2011; Gingras et al., 2014; Schubert, 2004). However, this study was the first to show the mediating effect.

The mediating effect of Pleasantness was also present, although it was somewhat weaker than the mediating effect of the Intensity of emotions. This finding confirms results of Talarico et al. (2004) who found that the strength of the emotional experience affects autobiographical memories more than the pleasantness of the experience does. Moreover, the relationship between pleasantness and autobiographical memories has not been fully consistent in previous literature. More pleasant memories are experienced as more vivid, more numerous (Berntsen, 1996), and older (Rubin & Berntsen, 2003) when compared to more unpleasant ones, especially when they are involuntary (Berntsen, 1998). On the other hand, memories of emotionally negative events have typically greater accuracy (Kensinger, 2009).

Based on previous literature, there are actually two possible ways how emotions can influence the strength and amount of MEAMs. First, the emotional experience and its intensity during the moment when a memory is formed may strengthen the consolidation of the memory and make it more vivid (Kensinger, 2009; McGaugh, 2013; Talarico et al., 2004). Second, the emotional experience of music when it is heard may make the retrieval of a memory more effective, especially when the music has been associated with some particular emotional experience (Buchanan, 2007; Schulkind et al. 1999). In both of these cases, emotions serve as a strengthening object between music and memories. Of course, it should be kept in mind, that the relationship has possible two-way causality. When recalling an autobiographical memory which is personally important or specifically related to the song, it has great chance to elicit strong emotions (Buchanan, 2007; Schubert, 2004). However, in that case it is not the music that evokes emotions, but memories (despite evoked by music).

On neural level, it has proposed that the medial prefrontal cortex participates in emotional processing along with processing of music and autobiographical memories (Janata, 2009). It could be a critical area in merging these different processes together on a conceptual level. Also, as pointed out before, this area does preserve long without much cortical atrophy in people with Alzheimer's disease, so it is likely that it contributes to the well known effect of music as a strong elicitor of emotions in persons with dementia. While the results of this study are behavioural, the high correlations between emotional ratings and Autobiographical salience do raise the importance of this potential explanation.

Intuitively, familiarity of music should have very strong connection to MEAMs. However, in the study by Janata et al. (2007) it was found that not all songs that evoke autobiographical memories are familiar to the listener, and vice versa. In the present study, the correlation between Familiarity and Autobiographical salience was nevertheless high ($r = .84$) when compared to the correlation ($r = .54$) reported by Janata et al. (2007). The relationships between emotions and familiarity were not emphasized in present study, but it should be noted that, because Familiarity and Autobiographical salience were so strongly correlated, it is possible that familiarity with the song could have affected the mediation effect of Intensity of emotions somehow. For example, a prior research has shown that some specific emotions, such as nostalgia, have a relation to both familiarity and autobiographical memories (Barrett & Janata, 2016). Ali and Peynircioglu (2010) found some evidence in one experiment that familiarity of music increased emotional intensity. In another experiment, the same effect was not found. This should be noted because Familiarity was originally very left-skewed in our data, as most of the songs were very known to the subjects and only a small portion were generally unfamiliar.

4.3 Strengths and limitations

The limitation and, at the same time, the strength of this study was its subject population. While all subjects were over 60 years old, about two-thirds of them singed in a choir and almost three-fourths of them had some other recent musical activity, the results can not be straightforwardly generalized to the whole population. It is possible that musical activity has some effect on how people perceive some aspects of music, for example musical phrases (Neuhaus, Knösche, & Friederici, 2006; Zhang, Jiang, Zhou, & Yang, 2016). Age has also its effect on musical experiences. Emotional music has been found to have greater effect on older than younger adults (Schulkind et al., 1999; Schulkind & Woldorf, 2005) and the music culture has been diverse during different decades. However, because the age range of the study population was limited, the results could have more power to predict autobiographical saliency and perceived familiarity of music for this particular age group.

Concerning emotional ratings, it is possible that some participants rated emotions that they think the music should convey, instead of the emotions that the music subjectively elicited. This could have affected the responses in this study some way, although we particularly asked people to rate elicited emotions. When people are asked to rate the intensity of musical emotions, there could be a tendency to rate conveyed emotions to be stronger than elicited emotions, which may have some influence on ratings (Ali & Peynircioglu, 2010). The same problem applies to all research designs using questionnaire-type responses in the context of music.

As an another methodological limitation, the PCA, which was applied to form the musical components, creates linear combinations of original variables, such as the musical features in this study. That means that although some of them have much stronger loadings on specific components than others, all of the original features have some influence on every component. Thus, interpreting only the variables with strongest loadings leaves us with some ambiguity about the influence of the other variables. However, leaving only small weighting variables out of interpretation is not as harmful as having a multicollinear and overfitted explanatory variables. Overall, it looks like short-time features, or low-level features as called in some texts, are generally better explainers independent of the behavioral or cognitive dimensions studied (aside this study, Gingras et al., 2014). Of the four original long-time features, only pulse clarity were able to explain some linear relationships in the data.

In future, the findings of this study could potentially be used to enhance music rehabilitation and care practices of people with neurological conditions who cannot communicate their musical needs. For example, music can help patients with Alzheimer’s disease to recall autobiographical memories, and also with patients suffering from severe depression, schizophrenia or other populations with possible autobiographical memory decline (El Haj et al., 2012). Music listening can also improve mood, orientation and cognitive functions in people with mild or moderate dementia (Särkämö et al., 2014). The knowledge about musical features and their relationship with memory could help the selection of right music for people suffering mental and neurological problems.

Yet, it is possible that if the experiment would be carried out using a clinical (patient) subject group instead of healthy one, age-related neurological problems, such as cortical atrophy, may have some influence on the results. This is unlikely to influence the relationship between musical features and Autobiographical salience since most of the songs evoked autobiographical memories, which are typically well preserved in Alzheimer’s disease or similar problems (El Haj et al., 2012). However, changes in emotional processing may potentially alter the results in a clinical population, and that possibility should be addressed in future studies.

4.4 Conclusions

Present study demostrated some of the previously found effects of music on emotional responses, but found also novel relationships between musical features and MEAMs and familiarity of music. The approach of the present study was largely exploratory, as there was insufficient prior research to form specific hypotheses about the relationships. As a somewhat surprising result, the narrower spectrum, weaker pulse and less low-middle frequency fluctuation were related to more pleasant and intense emotions and stronger autobiographical memories. While effect sizes were strong enough to assume that the found relationships are real, future research about the topic is needed to prove these results via replications. The possible two-way causality between emotional reactions and MEAMs should also be examined in future. However, the results give an interesting, novel view to the MEAMs from the standpoint of musical features and emotions, which also has possible applications in the use of music listening in health care settings.

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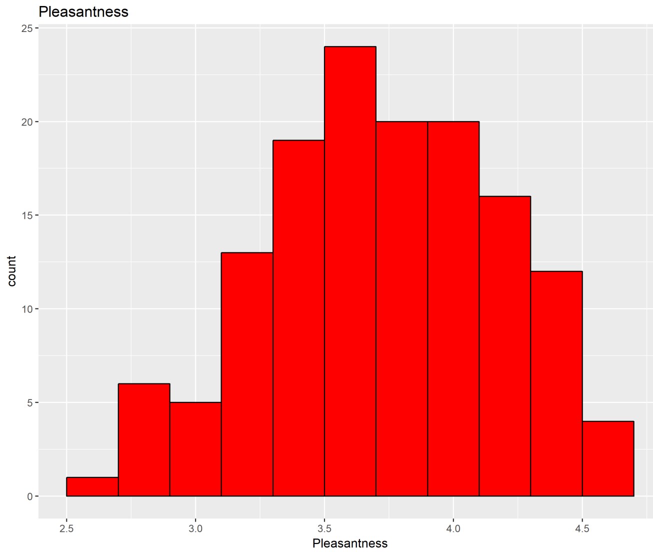
Appendix A. List of the songs used in the study.

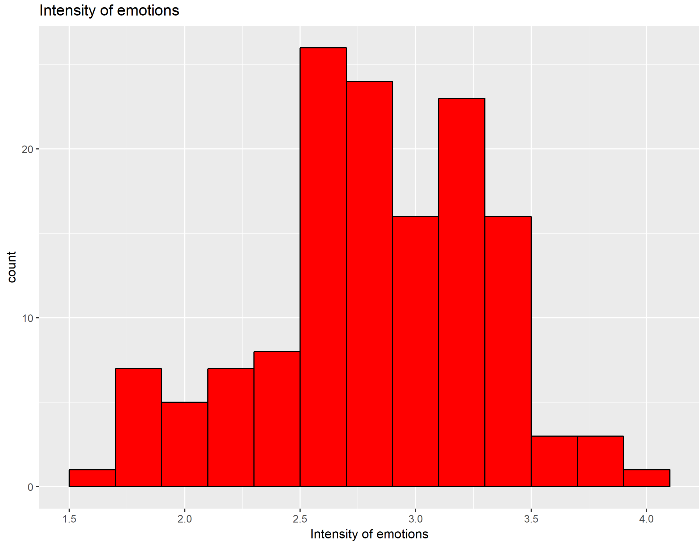
Table A1. List of the songs used in the study divided by decades.

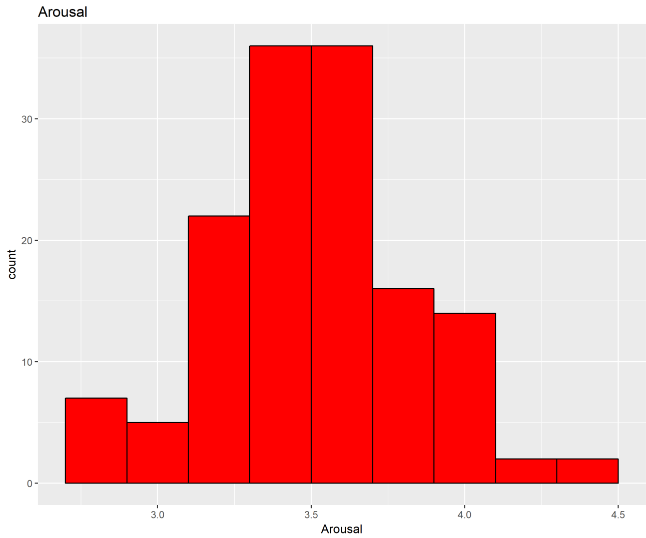
1950		1960	
Pirkko Jaakkola	*Pariisin taivaan alla*	Tamara Lund	*Sinun omasi*
Laila Kinnunen	*Lazzarella*	Katri Helena	*Minne tuuli kuljettaa*
Eila Pienimäki	*Vanhan veräjän luona*	Reijo Taipale	*Tähdet meren yllä*
Kipparikvartetti	*Kaunis Veera*	Mauno Kuusisto	*Kertokaa se hänelle*
Olavi Virta	*Sokeripala*	Danny	*Piilopaikka*
Juha Eirto	*Tiikerihai*	Kari Kuuva	*Tango pelargonia*
Eero Väre	*Kultainen nuoruus*	Four Cats	*Suuret setelit (Greenback dollar)*
Lasse Liemola	*Anna pois*	Dusty Springfield	*You don't have to say you love me*
Doris Day	*What ever will be, will be [Que sera, sera]*	Billy J. Kramer & The Dakotas	*Bad to me*
The Platters	*Smoke gets in your eyes*	The Monkees	*I'm a believer*
Little Richard	*Long tall sally*	The Rolling Stones	*The last time*
Harry Belafonte	*Day O (Banana boat song)*	The Animals	*House of the rising sun*
Nat King Cole	*Quizas, quizas, quizas*	The Swinging Blue Jeans	*Hippy hippy shake*
Louis Armstrong	*Mack the knife*	Stan Getz & Joao Gliberto	*The girl from Ipanema*
Chris Barber	*Petite fleur*	Ray Charles	*Hit the road Jack*
Metro-tytöt	*Orvokkeja äidille*	Vieno Kekkonen	*Ei koskaan sunnuntaisin*
Helena Siltala	*Ranskalaiset korot*	Pirkko Mannola	*Kuinka rakkaus alkoi*
Annikki Tähti	*Kuningaskobra*	Pasi Kaunisto & Nacke Johansson's Orchestra	*Koskaan et muuttua saa*
Brita Koivunen	*Suklaasydän*	Eino Grön	*Sä kuulut päivään jokaiseen*
Tapio Rautavaara	*Isoisän olkihattu*	Aikamiehet	*Iltatuulen viesti*
Kauko Käyhkö	*Rovaniemen markkinoilla*	Johnny Forsell	*Hyvin menee kuitenkin*
Georg Ots	*Saarenmaan valssi*	Eero Raittinen	*Vanha holvikirkko*
Veikko Tuomi	*Vanhan vaahteran laulu*	The Sounds	*Emma*
Rosemary Clooney	*Mambo italiano*	The Beatles	*All my loving*
Pat Boone	*Love letters in the sand*	Tom Jones	*Delilah*
Bill Haley	*Rock around the clock*	Simon & Garfunkel	*Bridge over troubled water*
Elvis Presley	*Heartbreak hotel*	Procol Harum	*A whiter shade of pale*
The Foud Lads	*Istanbul [Not Constantinople]*	The Beach Boys	*Good vibrations*
Louis Prima	*Buona Sera*	The Renegades	*Cadillac*
Glenn Miller	*Moonlight serenade*	Aretha Franklin	*Chain of fools*
1970		**1980**	
Vicky Rosti	*Tuolta saapuu Charlie Brown*	Paula Koivuniemi	*Tummat silmät, ruskea tukka*
Merja Rantamäki	*Mistä mä löytäisin sen laulun*	Vera Telenius	*Miljoona ruusua*
Jukka Kuoppamäki	*Kultaa tai kunniaa*	Topi Sorsakoski	*Eeva [Eva]*
Jussi & the Boys	*Metsämökin tonttu*	Kirka	*Surun pyyhit silmistäni pois*
Jari Huhtasalo	*Äideistä parhain*	Pirkka-Pekka Petelius	*Muistan sua Elaine*
Hector	*Olen hautausmaa*	Miljoonasade	*Marraskuu*
Jamppa Tuominen	*Aamu toi, ilta vei*	Leevi & the Leavings	*Pohjois-Karjala*
Irwin Goodman	*St. Pauli ja Reperbahn*	Pelle Miljoona	*Moottoritie on kuuma*
ABBA	*Waterloo*	Barbara Streisand	*Woman in love*
Lynn Anderson	*Rose garden*	Madonna	*Papa don't preach*
Elton John	*Crocodile rock*	Toto	*Africa*
The Rubettes	*Sugar baby love*	David Bowie	*Let's dance*
Creedence Clearwater Revival	*Travelin' band*	Earth, Wind & Fire	*Celebration*
Donna Summer	*Hot stuff*	Gaye Marvin	*I heard it through the grapevine*
Carl Douglas	*Kung fu fighting*	Diana Ross	*Upside down*
Katri Helena	*Syysunelma*	Tuula Amberla	*Lulu*
Fredi	*Puhu hiljaa rakkaudesta*	Lea Laurila	*Ei oo, ei tuu*
Erkki Junkkarinen	*Ruusuja hopeamaljassa*	Matti & Teppo	*Mä näitä polkuja tallaan*
Kai Hyttinen	*Dirlanda (Dirlada)*	Rauli Badding Somerjoki	*Tähdet tähdet*
Leevi & the Leavings	*Mitä kuuluu, Marja-Leena?*	Juice Leskinen	*Kaksoiselämää*
Tuomari Nurmio	*Valo yössä*	J. Karjalainen ja Mustat Lasit	*Doris*
Hurriganes	*Get on*	Juha Vainio ja Hyvän Tuulen Ajajat	*Albatrossi*
Kontra	*Jerry Cotton*	Eppu Normaali	*Kitara, taivas ja tähdet*
Baccara	*Yes sir, I can boogie*	Blondie	*Call me*
Middle of the road	*Chirpy chirpy cheep cheep*	Michael Jackson	*Billie Jean*
Uriah Heep	*Lady in black*	Tina Turner	*Typical male*
Christie	*Yellow river*	Deep Purple	*Black Night*
Led Zeppelin	*Whole lotta love*	Leonard Cohen	*Dance me to the end of love*
Roberta Flack	*Killing me softly with his song*	Ottawan	*Hand up*
Boney M.	*Rivers of Babylon*	Stevie Wonder	*I just called to say I love you*
Folk			
Tuoll' on mun kultani		*Taivas on sininen ja valkoinen*	
Kalliolle kukkulalle		*Soittajapaimen*	
Tuonne taakse metsämaan		*Kotini*	
Kotimaani ompi Suomi		*Lapsuuden toveriile*	
Yksi ruusu on kasvanut laaksossa		*Sunnuntaiaamuna*	
Leivo		*Jos sais kerran reissullansa*	
Säkkijärven polkka		*Minun kultani kaunis on*	
Tulatullallaa		*Täällä yksinäni laulelen*	
On neidolla punapaula		*On suuri sun rantas autius*	
Laulu Suomessa		*Heili Karjalasta*	

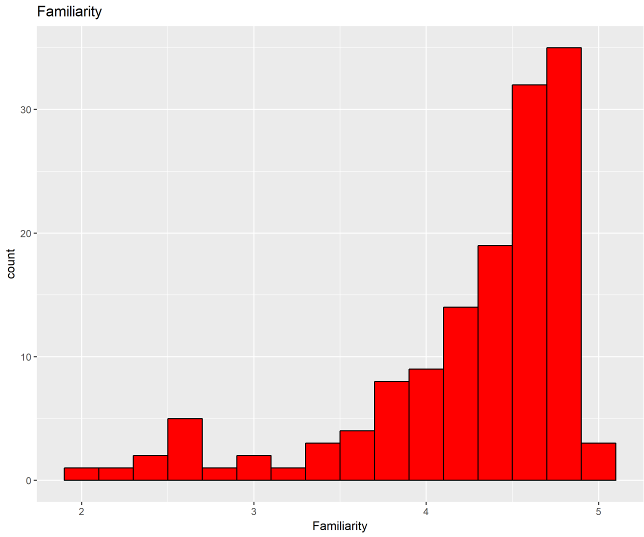
Appendix B. Distributions.

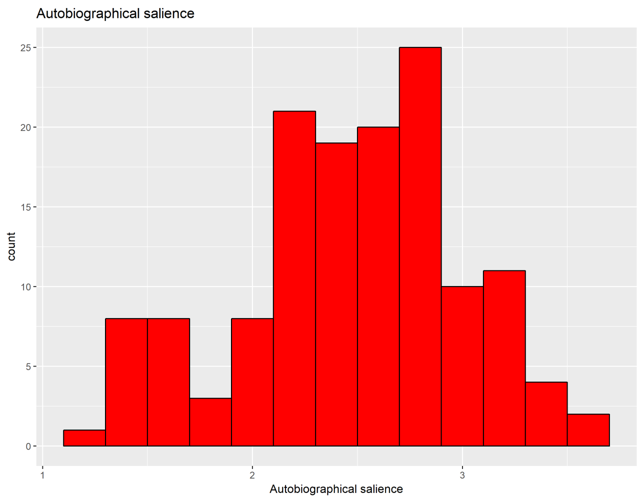
Distributions of rating variables



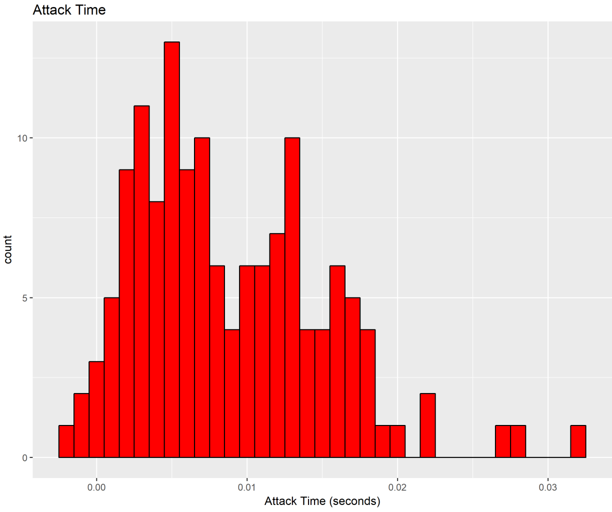


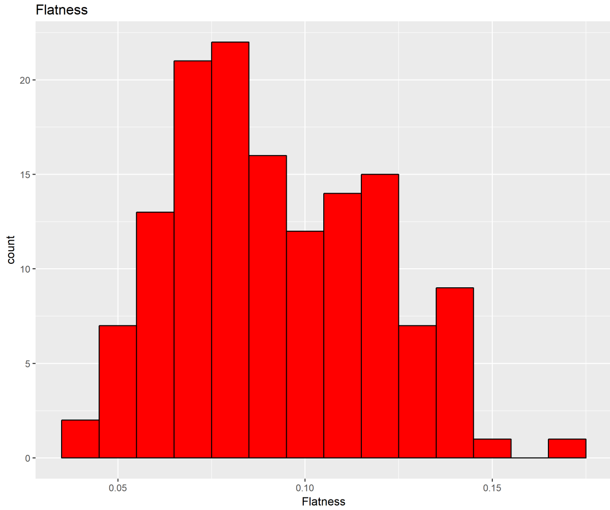


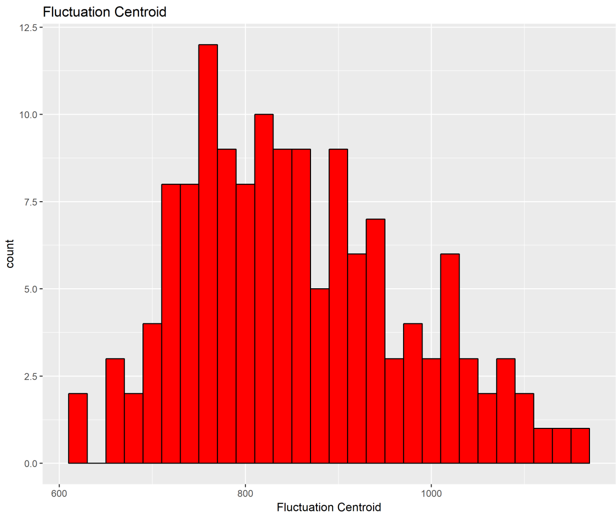


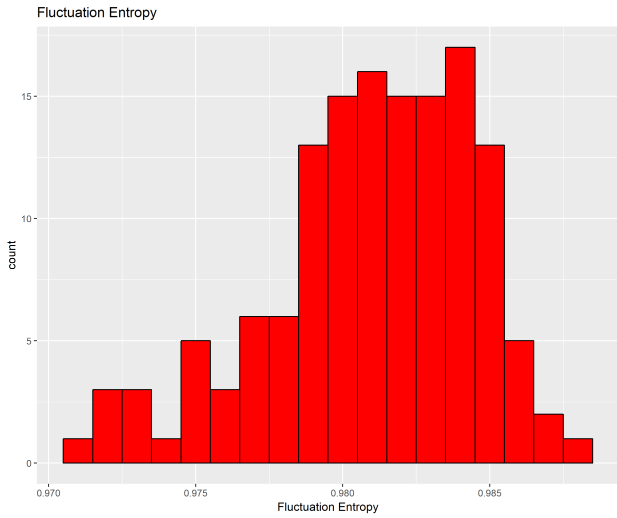


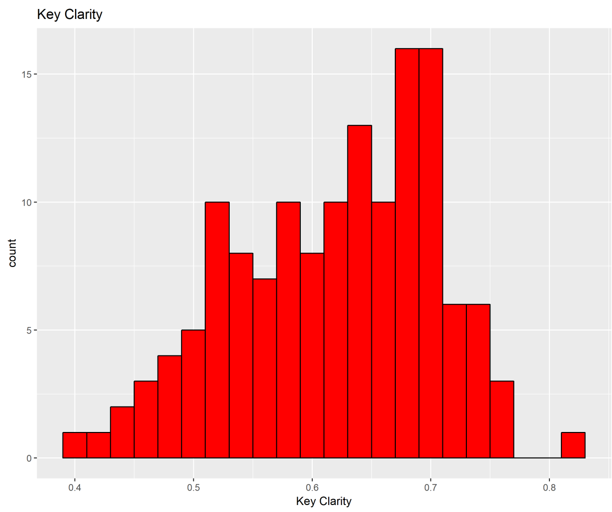
Distributions of musical features

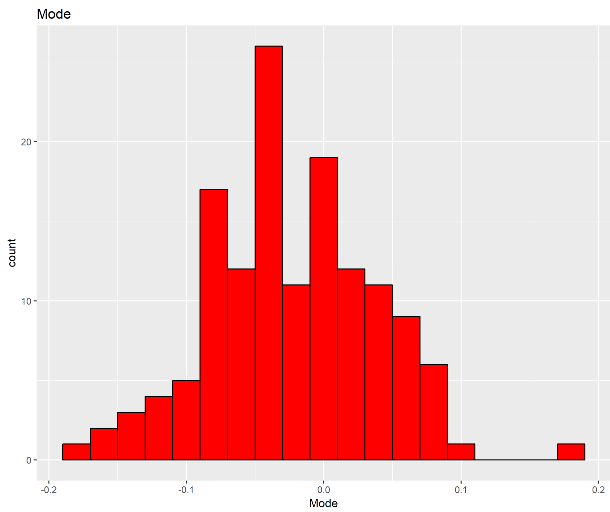


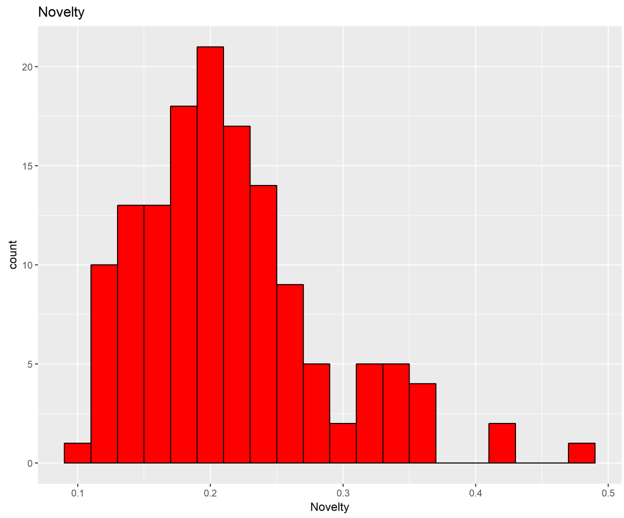
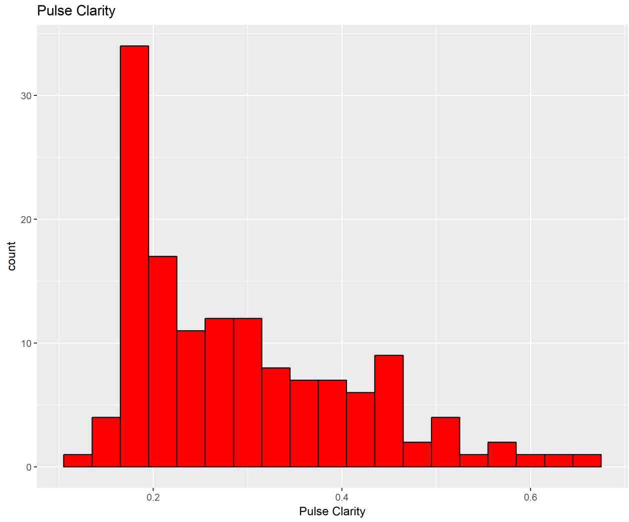
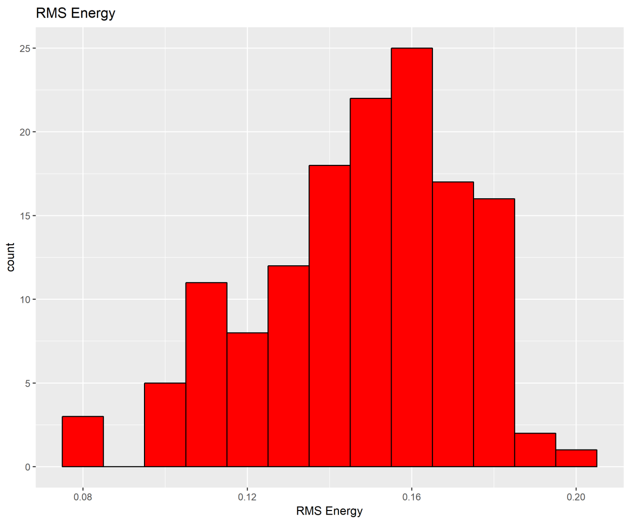
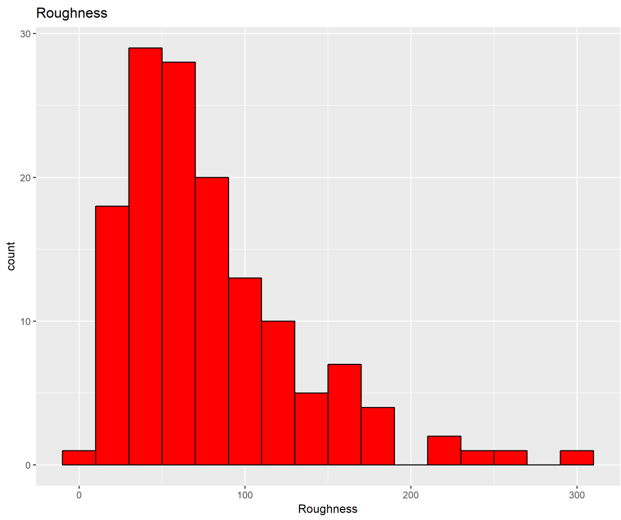
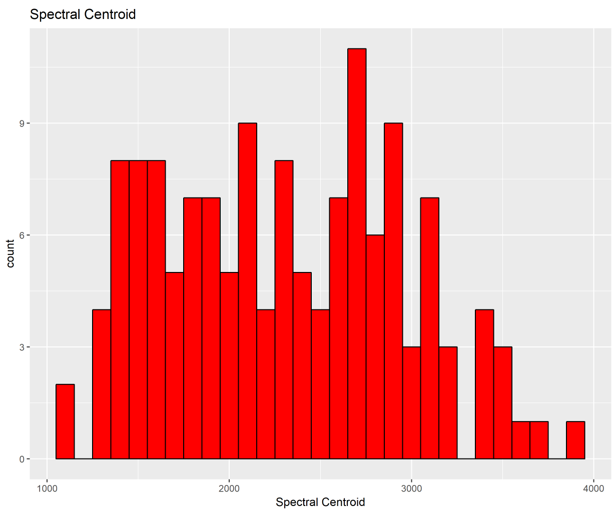
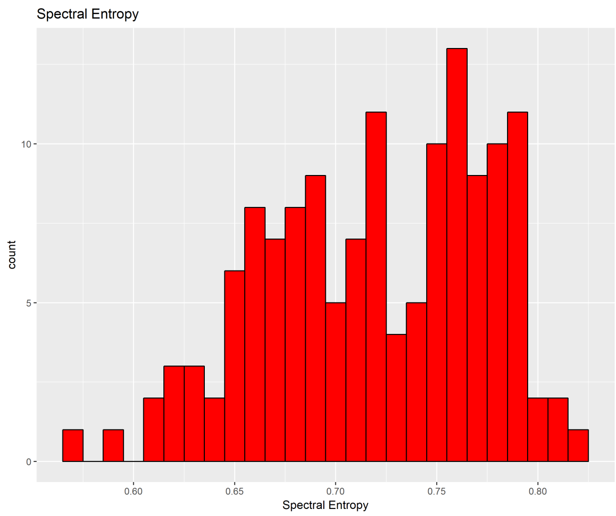


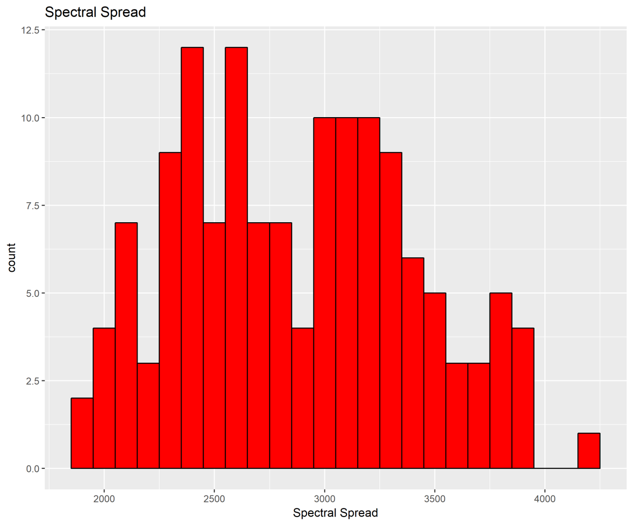


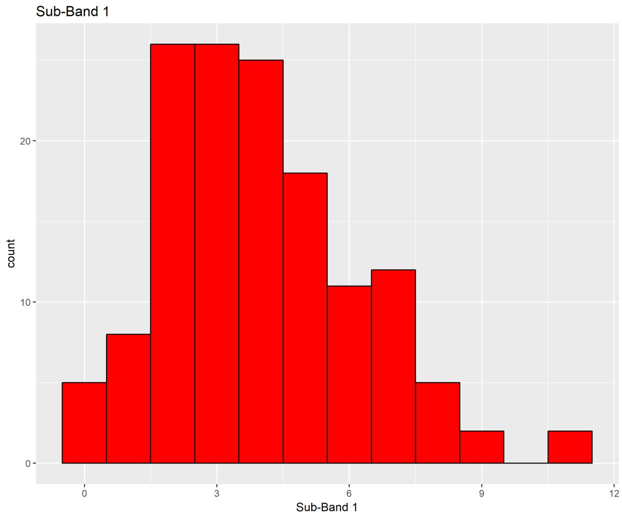


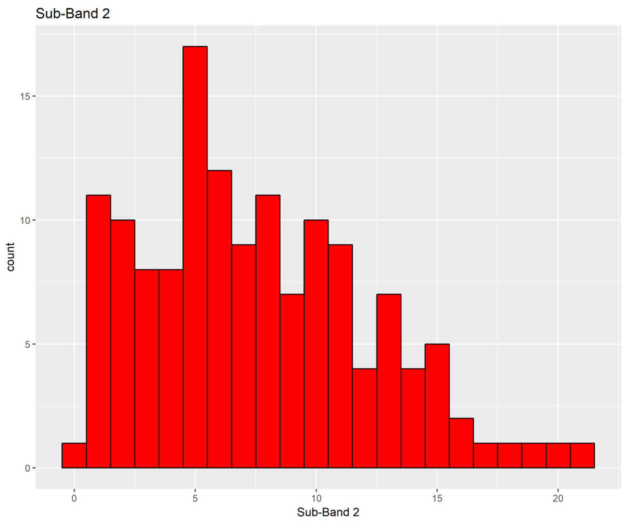


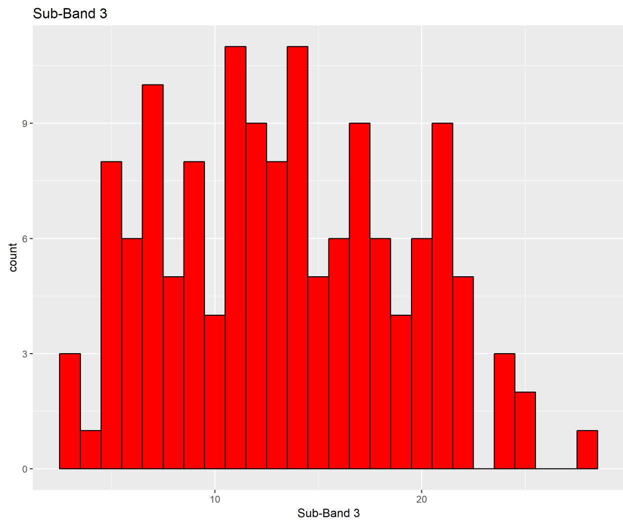


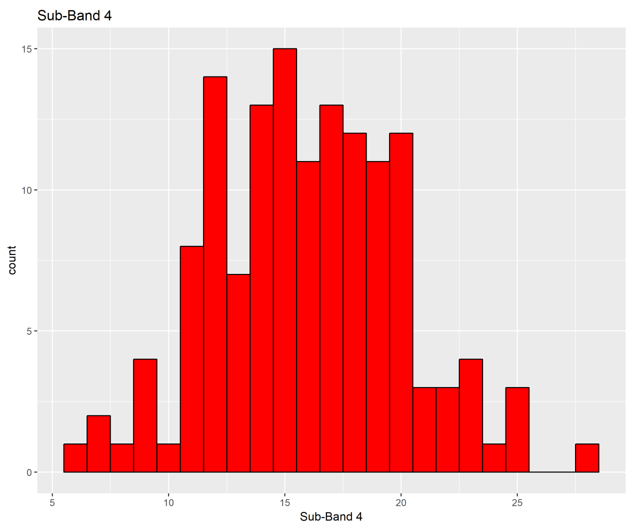

Novelty
count
Novelty

Pulse Clarity
count
Pulse Clarity

RMS Energy
count
RMS Energy

Roughness
count
Roughness

Spectral Centroid
count
Spectral Centroid

Spectral Entropy
count
Spectral Entropy

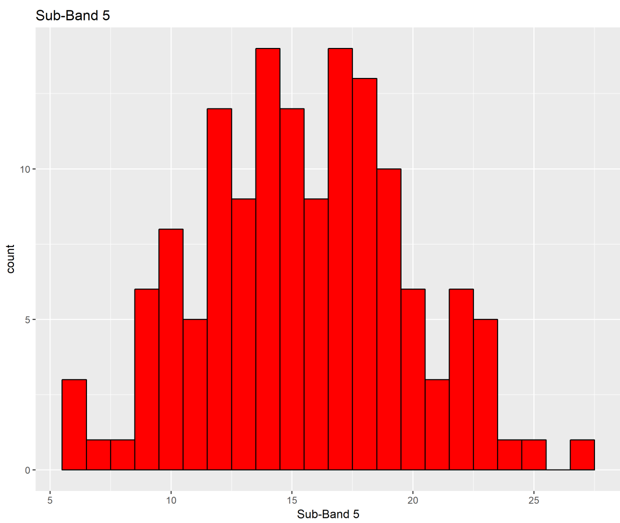

Spectral Spread
count
12.5
10.0
7.5
5.0
2.5
0.0
2000
2500
3000
3500
4000
Spectral Spread

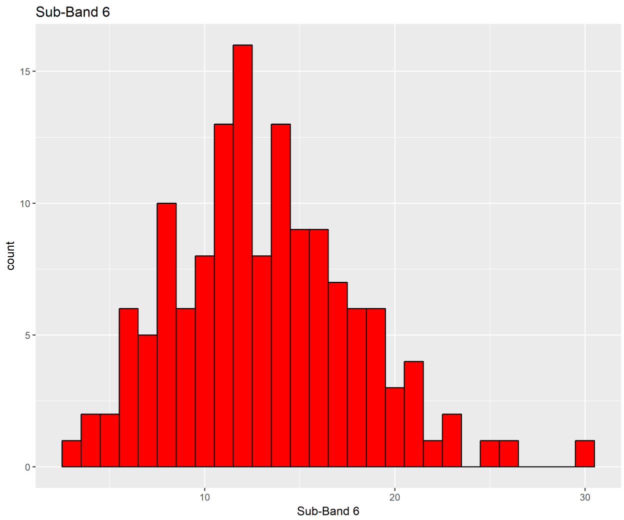

Sub-Band 1
count
20
10
0
0
3
6
9
12
Sub-Band 1

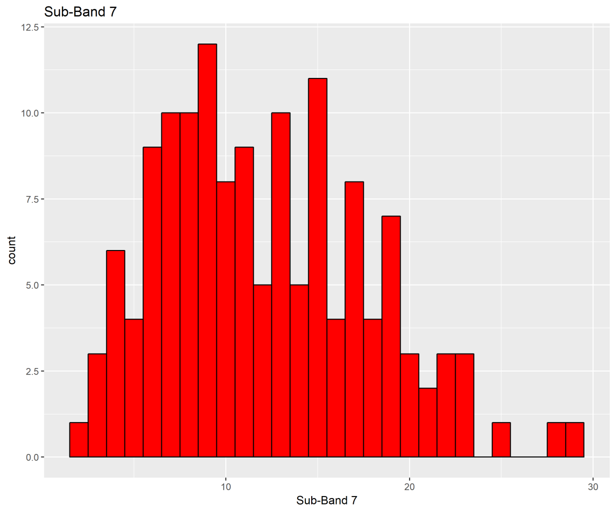

Sub-Band 2
count
15
10
5
0
0
5
10
15
20
Sub-Band 2

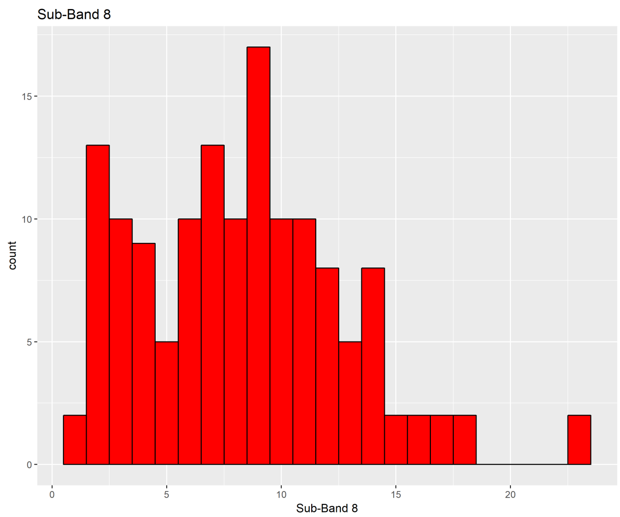

Sub-Band 3
count
9
6
3
0
10
20
Sub-Band 3

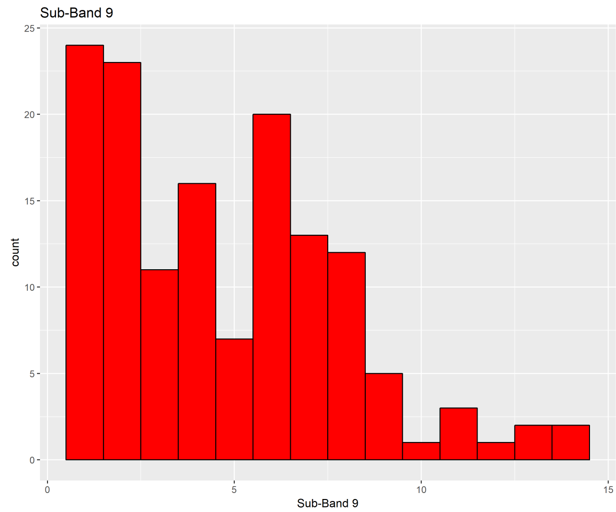

Sub-Band 4
count
15
10
5
0
5
10
15
20
25
Sub-Band 4

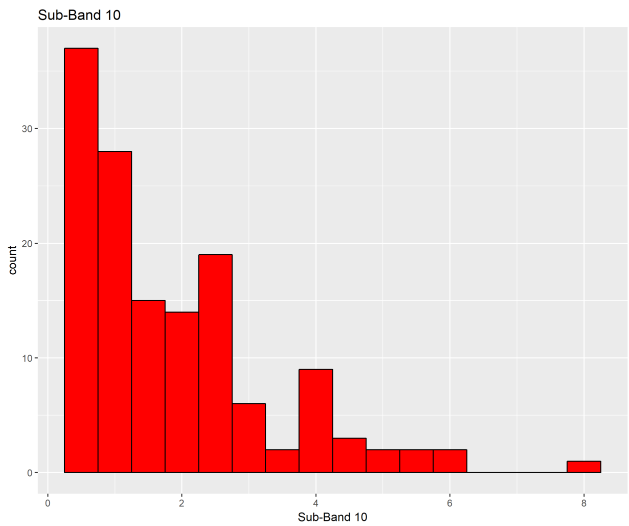

Sub-Band 5
count
10
5
0
5
10
15
20
25
Sub-Band 5


Sub-Band 6
count
Sub-Band 6

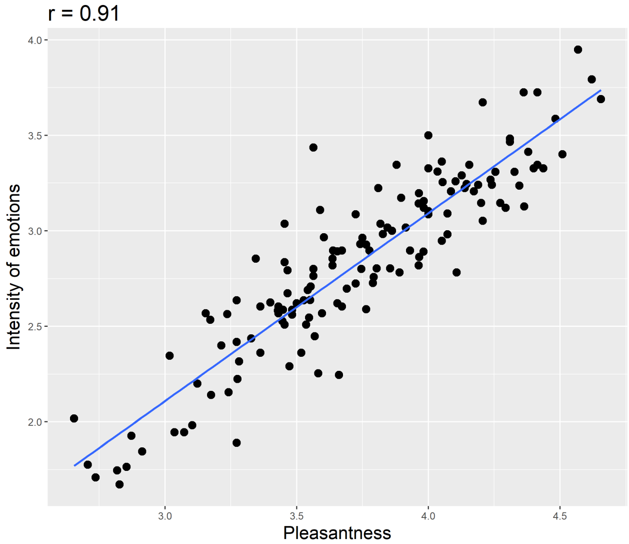

Sub-Band 7
count
Sub-Band 7

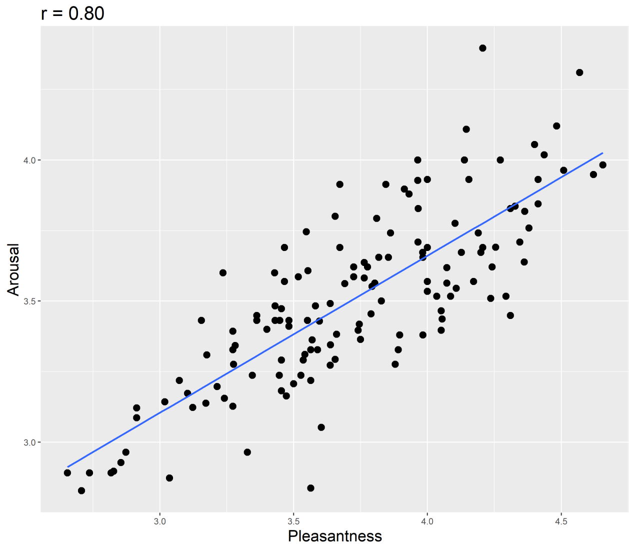

Sub-Band 8
count
Sub-Band 8

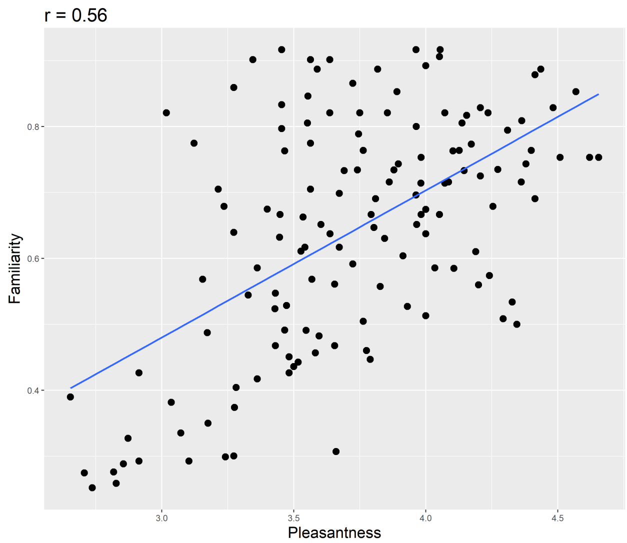

Sub-Band 9
count
Sub-Band 9

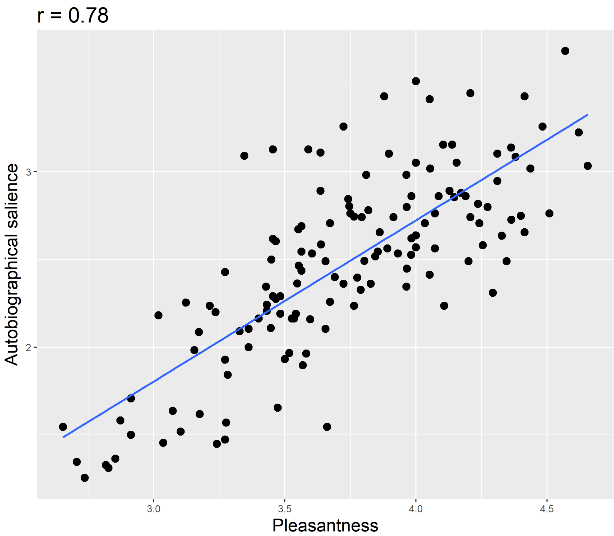

Sub-Band 10
count
Sub-Band 10

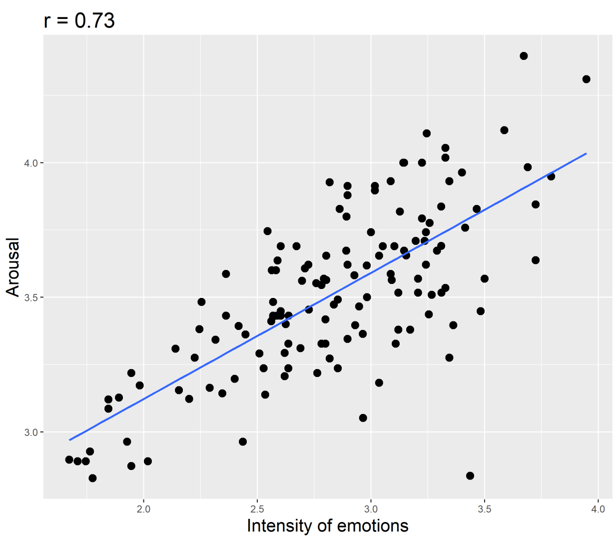
Appendix C. Scatterplots between ratings and musical components.

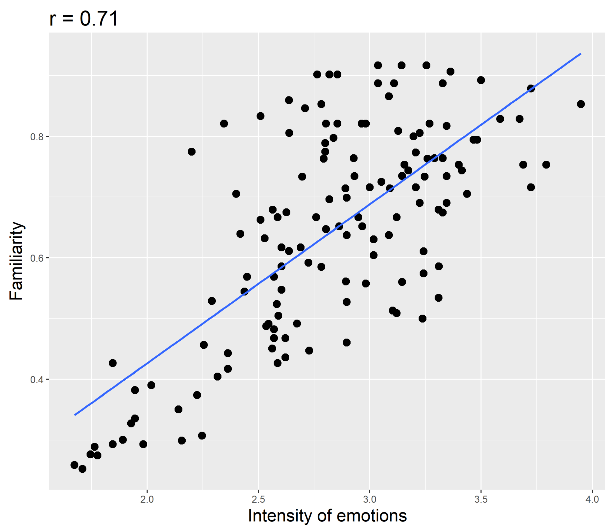


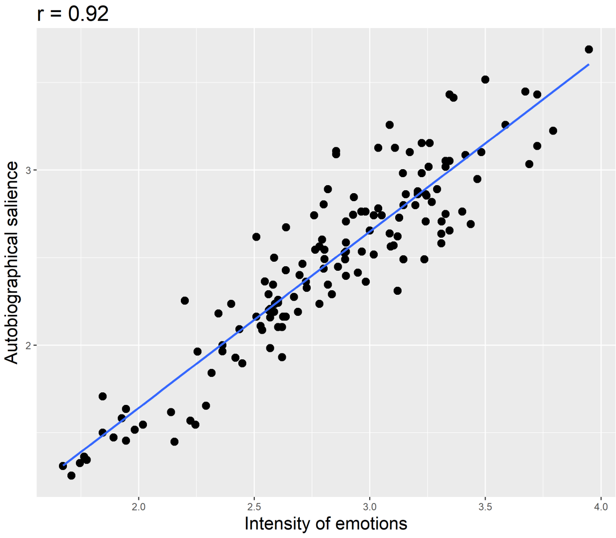


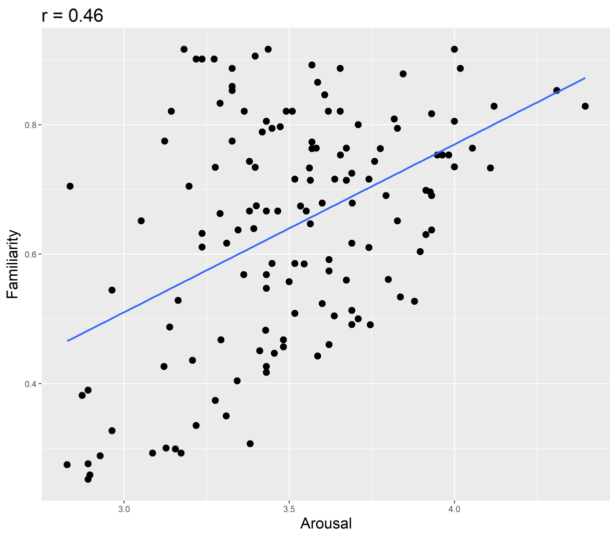


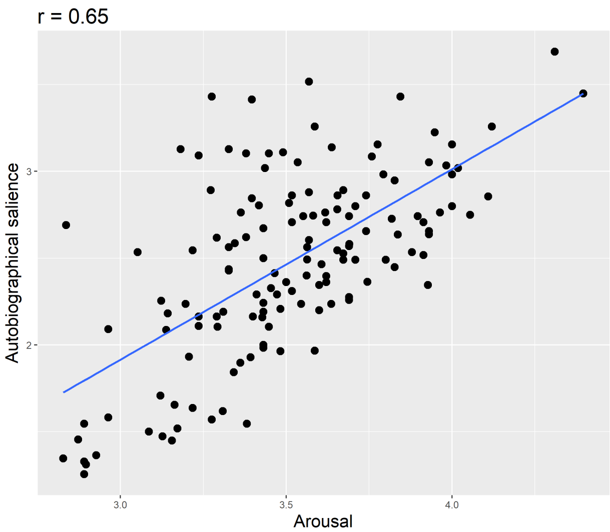


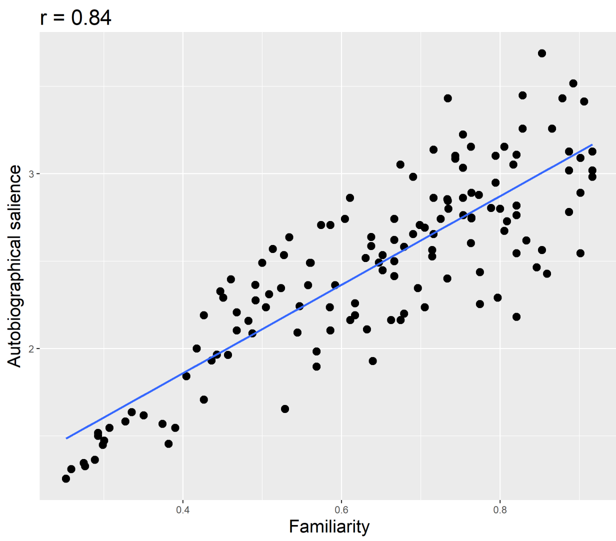


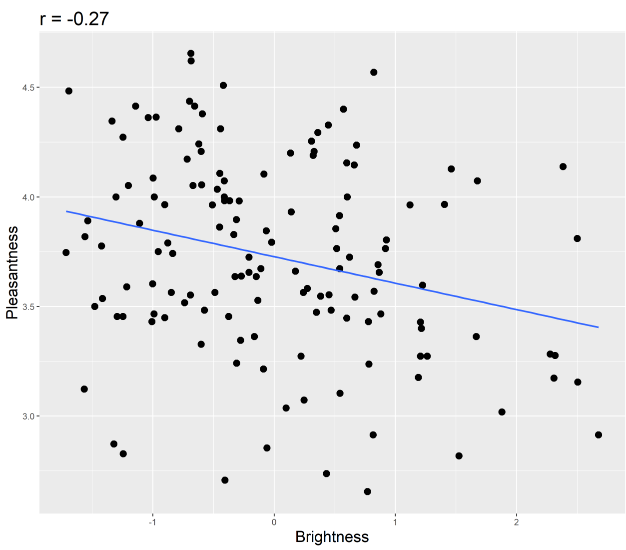


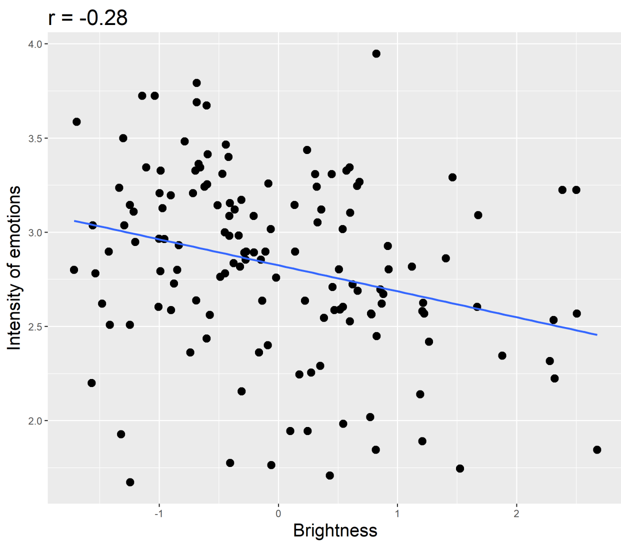

r = 0.92
Autobiographical salience
Intensity of emotions
2.0
2.5
3.0
3.5
4.0
2
3

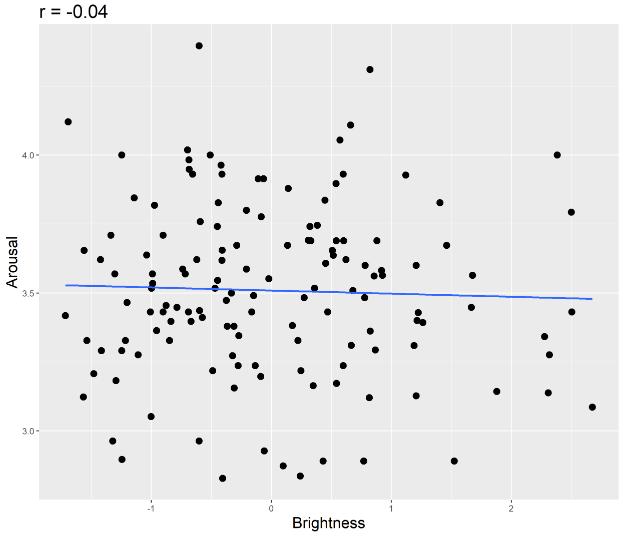

r = 0.46
Familiarity
Arousal
3.0
3.5
4.0
0.4
0.6
0.8

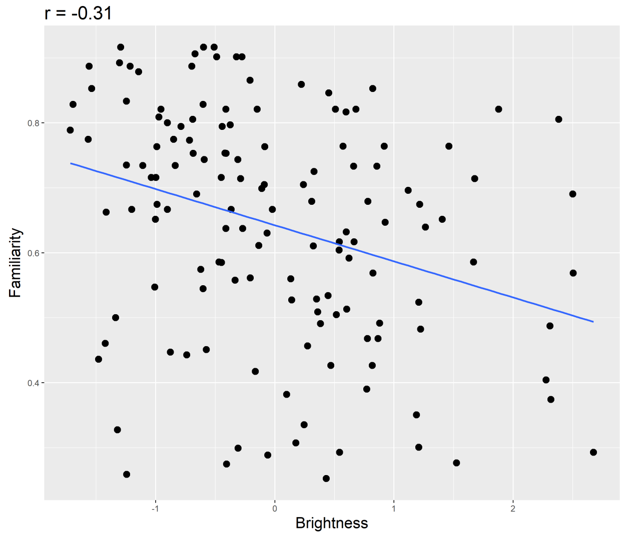

r = 0.65
Autobiographical salience
Arousal
3.0
3.5
4.0
2
3

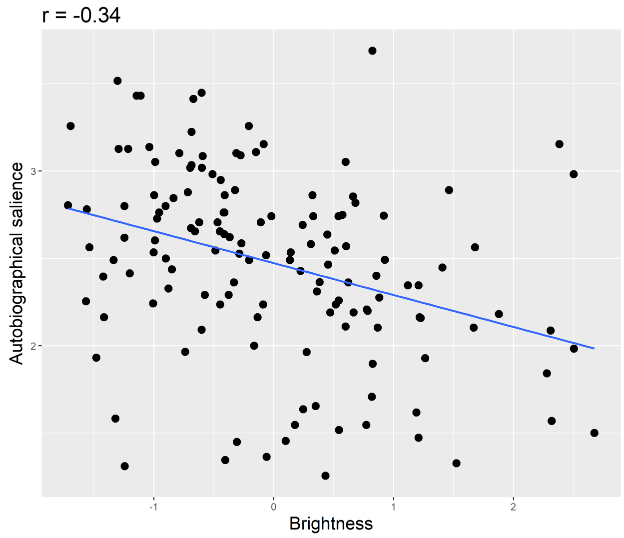

r = 0.84
Autobiographical salience
Familiarity
0.4
0.6
0.8
2
3

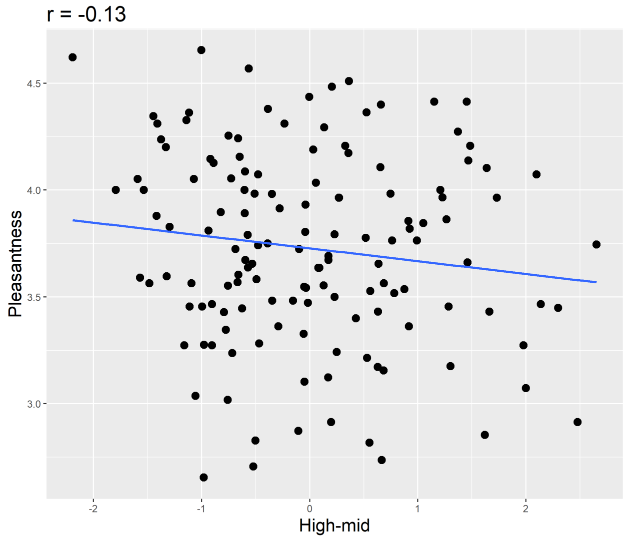

r = -0.27
Pleasantness
Brightness
-1
0
1
2
3.0
3.5
4.0
4.5

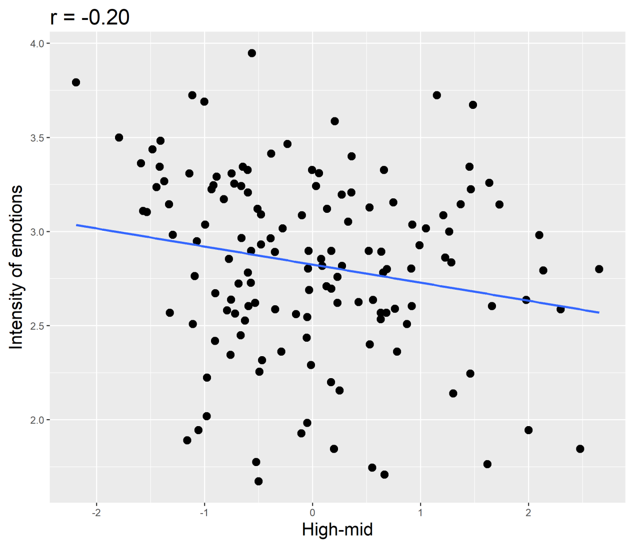

r = -0.28
Intensity of emotions
Brightness
-1
0
1
2
2.0
2.5
3.0
3.5
4.0

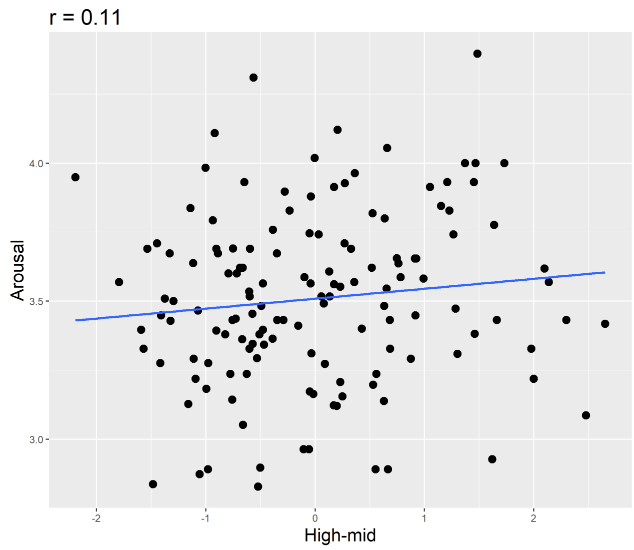

r = -0.04
Arousal
Brightness
4.0
3.5
3.0
-1
0
1
2

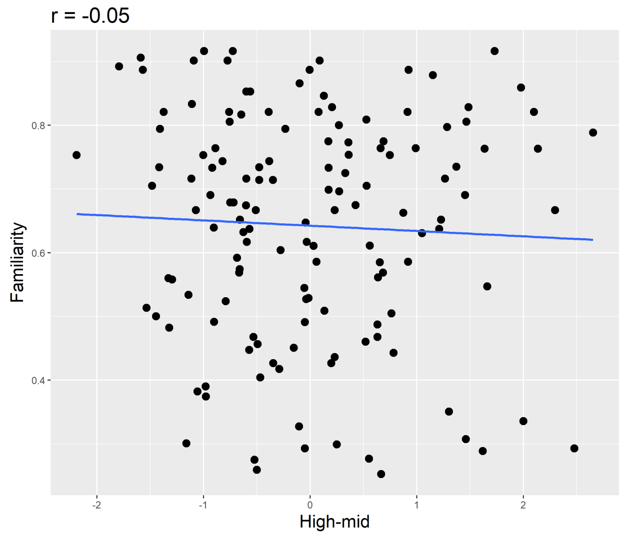

r = -0.31
Familiarity
Brightness
0.8
0.6
0.4
-1
0
1
2

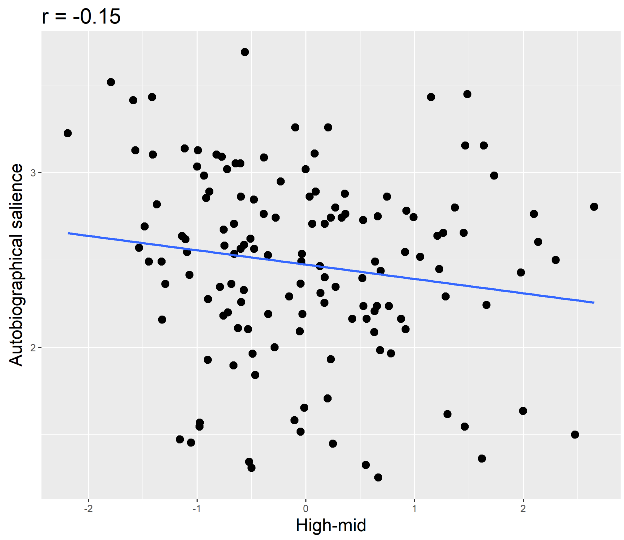

r = -0.34
Autobiographical salience
Brightness
3
2
-1
0
1
2

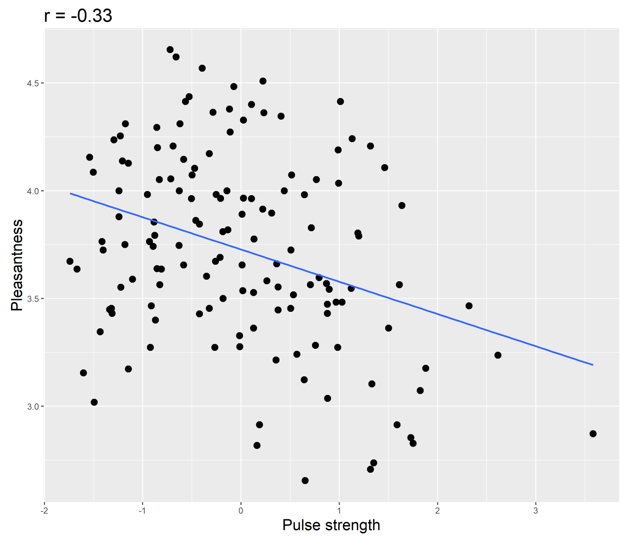

r = -0.13
Pleasantness
High-mid
4.5
4.0
3.5
3.0
-2
-1
0
1
2

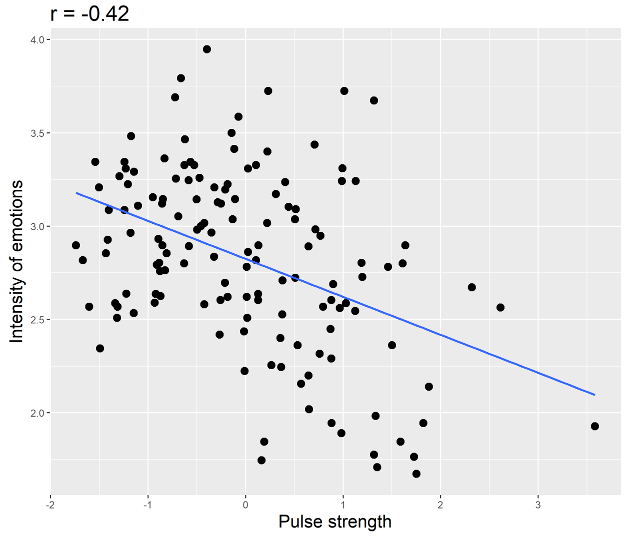

r = -0.20
Intensity of emotions
High-mid
4.0
3.5
3.0
2.5
2.0
-2
-1
0
1
2

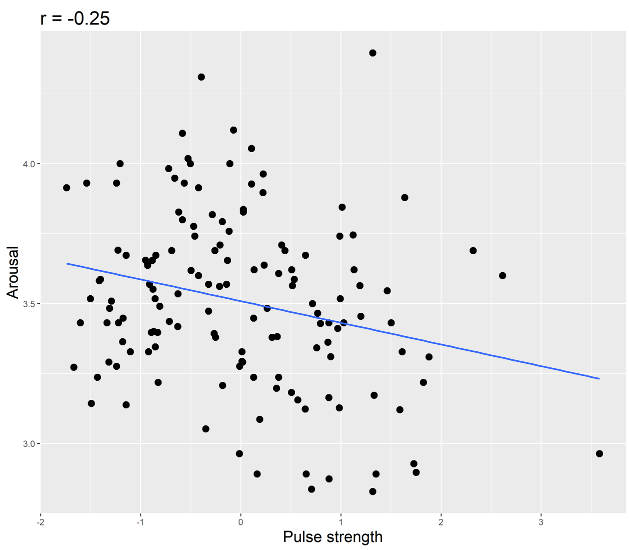

r = 0.11
Arousal
High-mid
4.0
3.5
3.0
-2
-1
0
1
2

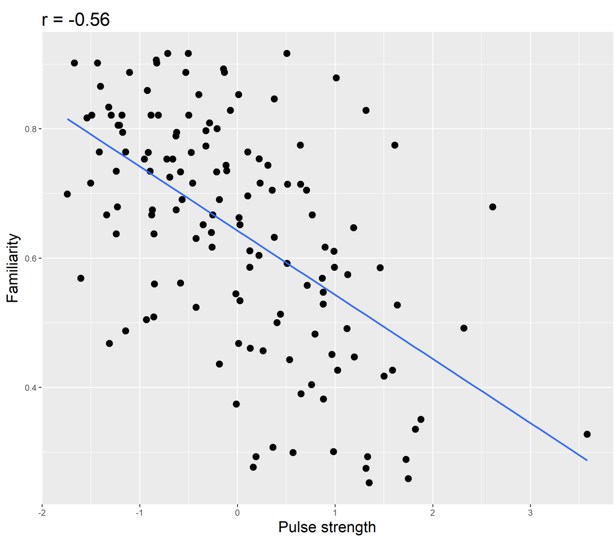

r = -0.05
Familiarity
High-mid

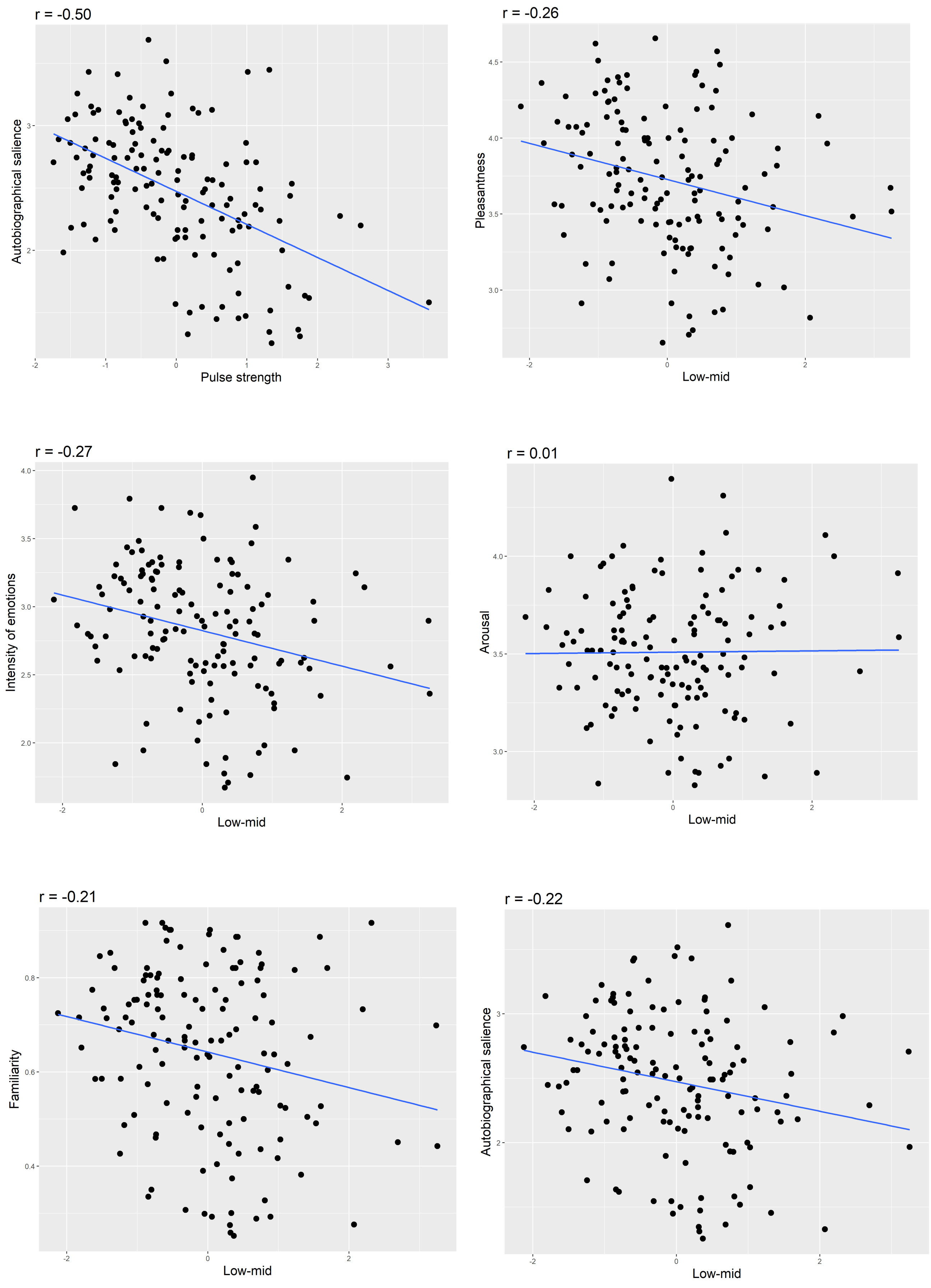

r = -0.15
Autobiographical salience
High-mid

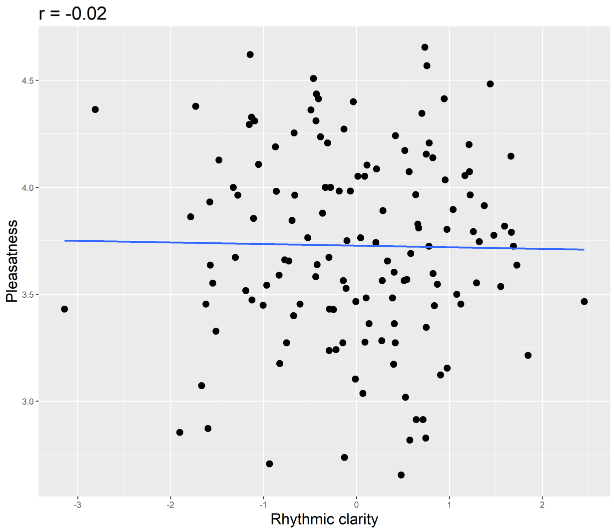

r = -0.33
Pleasantness
Pulse strength

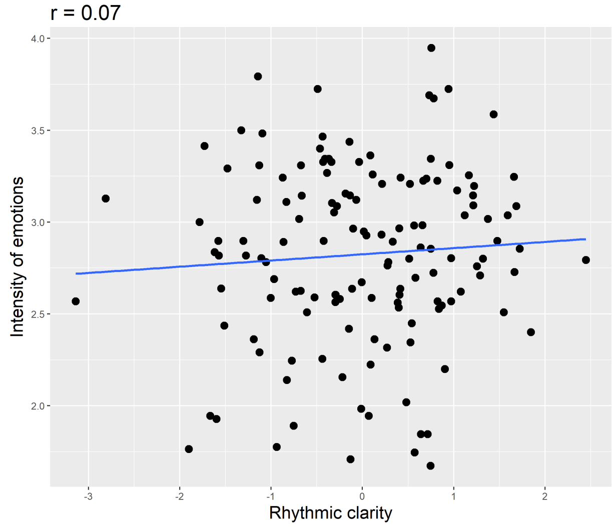

r = -0.42
Intensity of emotions
Pulse strength

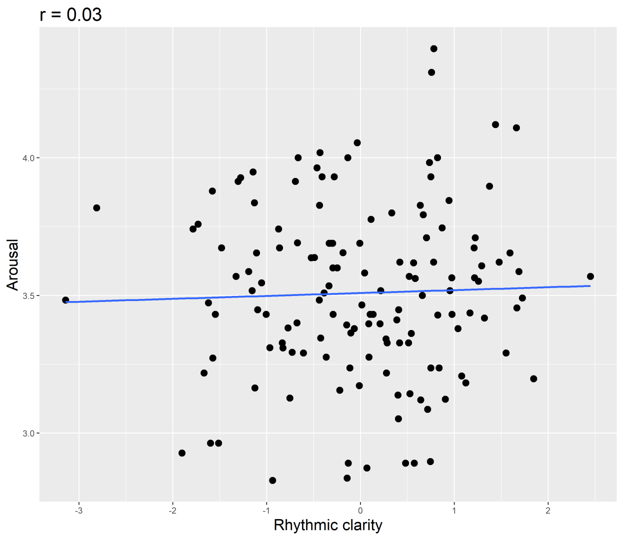

r = -0.25
Arousal
Pulse strength

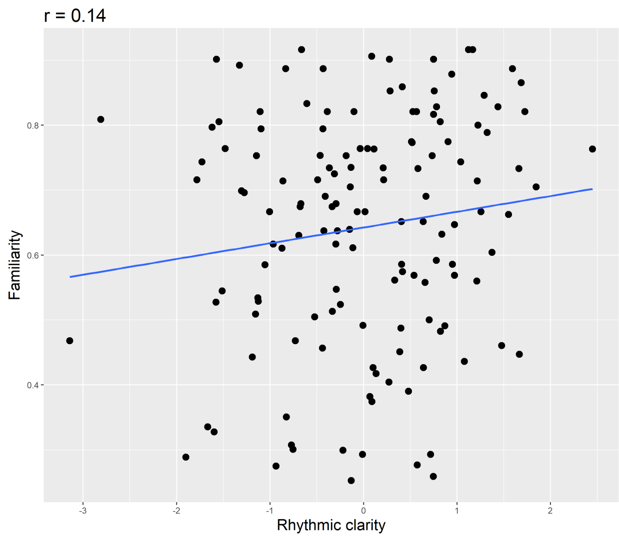

r = -0.56
Familiarity
Pulse strength

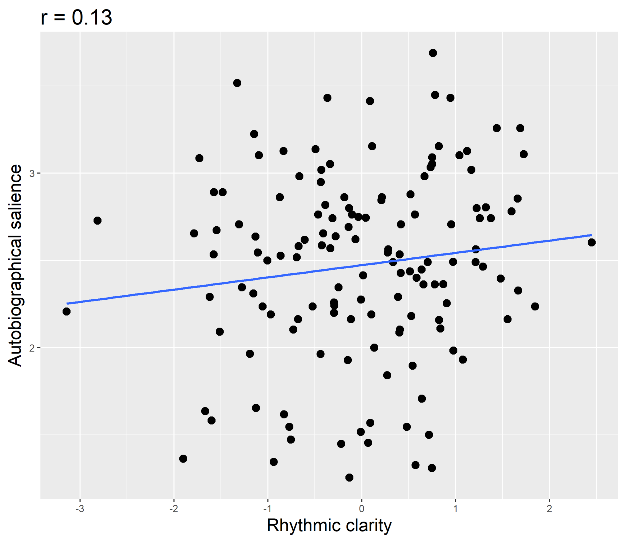

r = -0.50
Autobiographical salience
Pulse strength
r = -0.26
Pleasantness
Low-mid
r = -0.27
Intensity of emotions
Low-mid
r = 0.01
Arousal
Low-mid
r = -0.21
Familiarity
Low-mid
r = -0.22
Autobiographical salience
Low-mid

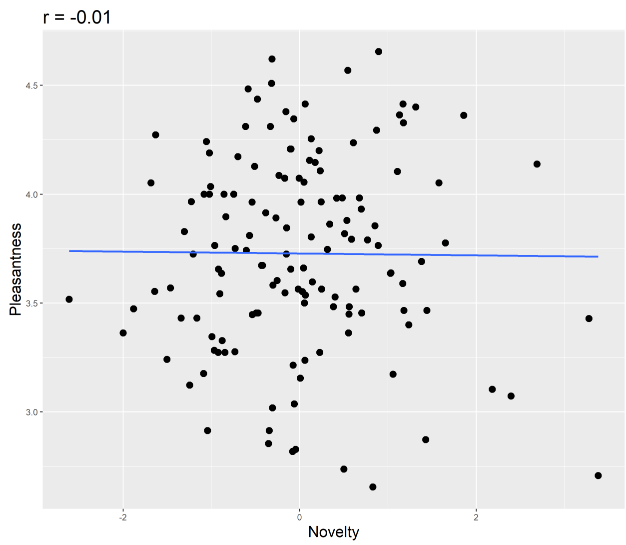

r = -0.02
Pleasatness
Rhythmic clarity

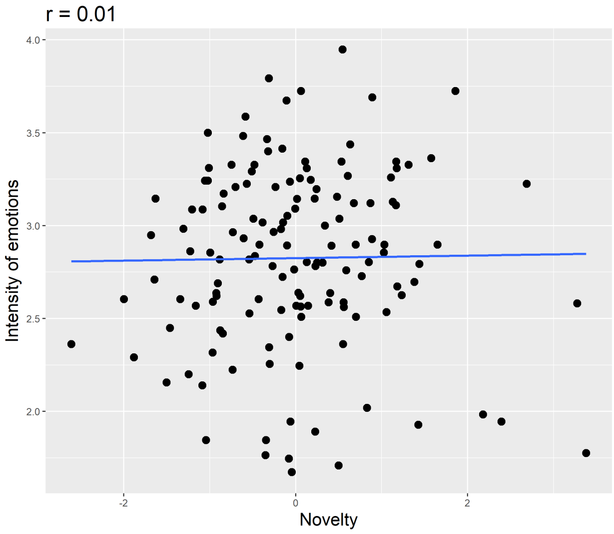

r = 0.07
Intensity of emotions
Rhythmic clarity

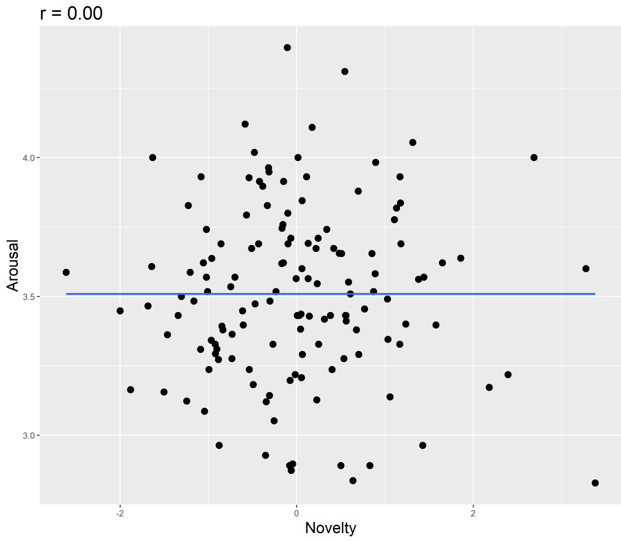

r = 0.03
Arousal
Rhythmic clarity

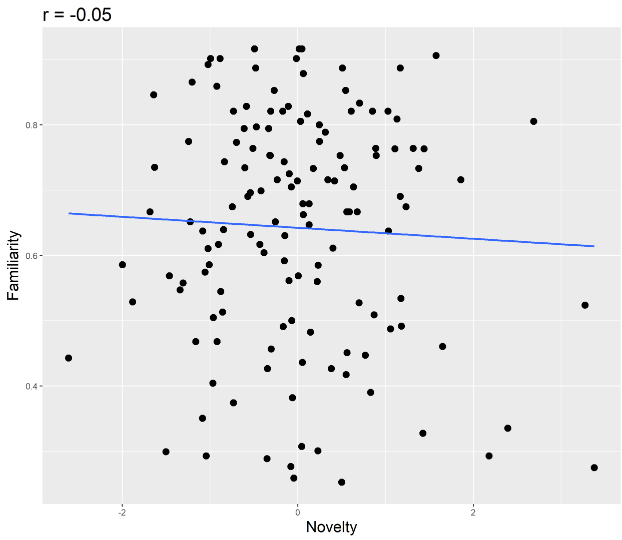

r = 0.14
Familiarity
Rhythmic clarity

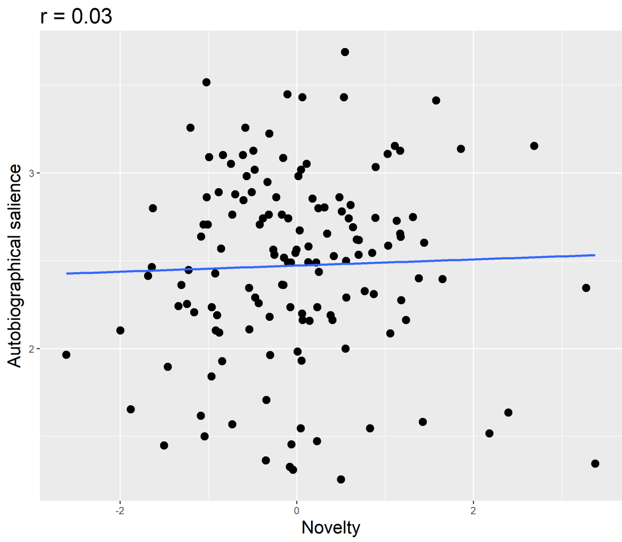

r = 0.13
Autobiographical salience
Rhythmic clarity


r = -0.01
Pleasantness
Novelty


r = 0.01
Intensity of emotions
4.0
3.5
3.0
2.5
2.0
-2
0
2
Novelty


r = 0.00
Arousal
4.0
3.5
3.0
-2
0
2
Novelty


r = -0.05
Familiarity
0.8
0.6
0.4
-2
0
2
Novelty


r = 0.03
Autobiographical salience
3
2
-2
0
2
Novelty